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Exploring AI adoption in manufacturing: An empirical study on effects of AI readiness

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ABSTRACT

Despite the promising potential of Artificial Intelligence (AI) in manufacturing, many companies remain hesitant to fully embrace this transformative technology, casting doubt on their preparedness for AI integration. While previous research has initiated the exploration of the relationship between AI readiness and AI adoption, empirical analyses in this domain are still scarce. To bridge this gap, we investigate how firms technological and organisational AI readiness, individually and in combination, influence the adoption of AI in manufacturing companies. Leveraging extensive empirical data from the *German Manufacturing Survey*, encompassing 1334 firms, we employ both descriptive and multivariate analysis. Our findings demonstrate that companies need to cultivate a robust AI readiness across both technological and organisational dimensions to facilitate successful AI adoption. Nevertheless, our approach unveils a gap between AI readiness and actual AI adoption: while manufacturing companies appear to have considerable levels of AI readiness, they are still reluctant to successfully implement AI in production processes. The results also show that companies are pursuing different strategies in the development of AI capabilities. Moreover, our analysis uncovers significant disparities among firms, highlighting the crucial role of certain firm-specific characteristics for AI adoption. Particularly interesting is our result about the u-shaped relationship between the company size and AI adoption as well as the relevance of the product complexity.

1. Introduction

The digital transformation of manufacturing is characterised by an increasing digitalisation of processes, automation as well as the integration of versatile digital technologies (Roblek et al., 2016; Li et al., 2017; Benner and Waldfogel, 2020; Oliveira et al., 2020). Advanced digital technologies are designed to help reduce the time and cost of production as well as generate new products and services (Verganti et al., 2020). AI, as one of these technologies, has gained attention across many sectors over the past few years promising significant potential for performance improvements (Mikalef et al., 2019b). We understand AI as the ability of systems to recognise patterns or irregularities and, accordingly, to propose or independently make decisions (Russell and Norvig, 2010; Toorajipour et al., 2021; Lerch et al., 2022; Merhi and Harfouche, 2024). In the narrow sense, we see AI as an innovation drawing on a range of technologies (such as machine learning or natural language processing (Collins et al., 2021)) that enable intelligent capabilities within an organisation. For manufacturing, the integration of AI solutions into production processes promises to improve productivity, flexibility, efficiency as well as enhanced automation of processes (Sanchez et al., 2020) in production areas such as process management, quality control or maintenance. However, although the promising potential of AI integration (Rammer et al., 2022; Bokrantz et al., 2023; Peretz-Andersson et al., 2024), its practical application in the production environment is at an early stage (Dohale et al., 2022) and manufacturing companies are currently still reluctant to utilise AI solutions (Lee et al., 2018; Holmström, 2022; Kinkel et al., 2022). This raises questions about the actual structural readiness of these organisations as well as their functional readiness to support the changes associated with the introduction of AI (Stevens, 2013).

A greater part of the literature acknowledges that the readiness of firms to adopt AI, and thus according to Rogers (2003) to actual use AI,

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can be analysed through the lenses of resources enabling a certain set of abilities (AI capabilities) (Mikalef and Gupta, 2021; Peretz-Andersson et al., 2024). Beyond the fundamental tangible resources i.e. technical prerequisites for AI adoption, such as the necessary data foundation and infrastructure, it is crucial to establish an organisational foundation and human resources to improve AI readiness (Pumplun et al., 2019; Jöhnk et al., 2021; Dohale et al., 2022). This, in turn, lays the groundwork for the development of AI capabilities. Therefore, literature highlights the significance of various intangible resources, including, for example, preparing the workforce and honing the necessary skills (Ghobakhloo and Ching, 2019; Drobot, 2020; Jöhnk et al., 2021), cultivating an open culture for new ideas (Dubey et al., 2020; Jöhnk et al., 2021), and leveraging collaboration to develop and implement suitable systems (Ghobakhloo and Ching, 2019; Jöhnk et al., 2021). By addressing these aspects, companies can enhance their readiness for AI integration in various contexts, laying the foundation for successful adoption and performance improvement.

Recent qualitative studies shed light on the process of resource orchestration through which manufacturing companies implement AI solutions (Horvat and Heimberger, 2022; Horvat et al., 2023; Peretz-Andersson et al., 2024). Additionally, numerous studies have analysed AI adoption in various corporate settings, providing valuable insights into the dynamics and factors of AI integration within companies (e.g. Kinkel et al. (2022), Chatterjee et al. (2021) or Pillai et al. (2022)). Furthermore, existing literature highlights the correlation between AI capabilities and firms' performance (Rialti et al., 2019; Mikalef and Gupta, 2021) as well as business model innovation (Sjödin et al., 2021). However, what remains less explored in recent literature is the intermediate step between AI readiness and AI capabilities (Dwivedi et al., 2021; Steininger et al., 2022). In other words, recent research has yet to fully clarify the connection between the availability of resources necessary for AI readiness and the actual adoption of AI solutions in companies, despite some initial efforts by Jöhnk et al. (2021) and Alsheibani et al. (2019). Furthermore, recent studies often lack explicit reference to the production context, leaving a gap in understanding the distinctive characteristics of this relatively traditional industry (Dwivedi et al., 2021). To address this research gap, this paper aims to answer the following research question:

How does the readiness of a firm for AI influence the likelihood of AI adoption in production processes of manufacturing firms?

Building upon the shared theoretical foundations of AI adoption (Chatterjee et al., 2021; Ghani et al., 2022; Kinkel et al., 2022) and AI readiness (Alsheibani et al., 2019; Jöhnk et al., 2021; Horvat and Heimberger, 2022; Heimberger et al., 2023; Horvat et al., 2023), we have constructed a conceptual framework to contextualise our study within current AI research. Within this framework, we have developed three measurement models to examine the impact of both technical and organisational AI readiness, as well as combined AI readiness, on the likelihood of a manufacturing company adopting an AI solution. The present study is conducted in the context of German manufacturing. Empirically, we use a representative large-scale survey conducted in 2022, which includes firm-level factual data reported by managers from 1334 manufacturing firms in Germany. Based on this comprehensive and robust empirical analysis; our primary focus lies in empirically testing the link between AI readiness and AI adoption, thus making an important contribution to current AI research in manufacturing and providing valuable insights for practitioners.

In a first step, we research into the degree to which manufacturing firms are primed to use AI into their production. Our descriptive findings underscore the importance of not only assessing AI readiness as a unified score but also delving into its components as distinct dimensions of readiness. By doing so, we contribute to the existing literature by empirically exploring the relevance of AI readiness as a combination of relevant technological and organisational resources, individually and in combination, for the actual adoption of AI solutions in production. Our descriptive analysis reveals that, despite a relatively high level of readiness for implementing this advanced digital technology, AI is not yet widely used in production processes. Therefore, employing robust logistic regression analysis, we delineate the varying significance of technological, organisational, and combined AI readiness in explaining the likelihood of AI adoption in production processes. In this multivariate analysis, we highlight that the adoption of AI is heavily influenced by the complexity of the manufactured products. We also show, while AI readiness emerges as a pertinent predictor for AI adoption among smaller firms, larger firms' adoption is predominantly shaped by factors such as firm size and the industry context, with AI readiness playing a rather limited role.

2. Conceptual background

2.1. AI adoption

The adoption of technological innovations has been analysed and applied in various disciplines for many decades. Research has focused on organisational processes (Pierce and Delbecq, 1977; Rogers, 1983; Klein and Sorra, 1996; Hameed et al., 2012) and factors (Tornatzky and Fleischer, 1990; Rogers, 1995) that describe or influence the adoption of innovations, as well as questions that analyse why some firms are more likely to adopt innovations than others (Damanpour and Schneider, 2006). Technology adoption has been examined across multiple contexts and analyses at the individual level and the organisational level have become particularly established (Oliveira and Marins, 2011; Pichlak, 2016). For example, models such as the Technology Acceptance Model (Davis, 1989), the Theory of Reasoned Action (Fishbein and Ajzen, 1975), the Theory of Planned Behavior (Ajzen, 1991), and the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003) are applied to analyse technology adoption at the individual level. In contrast, the Diffusion of Innovations (Rogers, 1983) and the Technology, Organisation, Environment (TOE) (Tornatzky and Fleischer, 1990) frameworks have been notably successful for analysing the organisation at firm level in order to study technology adoption (Oliveira et al., 2020).

Adoption analyses focus on a variety of technologies, such as e-business (Wu et al., 2003; Lin and Lin, 2008), cloud computing (Oliveira et al., 2014; Al-Hujran et al., 2018), and more recently, AI (Alsheibani et al., 2019; Bettoni et al., 2021; Rammer et al., 2022). The factors that enter and influence adoption frameworks and analyses vary depending on the specific context of each study (Oliveira and Marins, 2011). The emerging technology of AI is considered an innovation that organisations can choose to implement and hence require far-reaching adoption analyses. Within the realm of IT innovation adoption, the TOE model often serves as a basis for the classification of various factors into a framework in connection with AI adoption analyses (Chatterjee et al., 2021; Ghani et al., 2022; Kinkel et al., 2022; Merhi and Harfouche, 2024). Apart from that, there are other classifications of factors that influence organisations on their path to AI adoption, such as factors within the socio-technical system of people, processes and technology (Uren and Edwards, 2023).

While existing studies have delved into the analysis of specific AI adoption factors (Chatterjee et al., 2021; Ghani et al., 2022; Kinkel et al., 2022; Pillai et al., 2022), a gap persists in comprehensive empirical analyses that capture the current landscape of AI adoption within the manufacturing industry, particularly in the context of AI applications in production. Although some in-depth production related AI adoption papers already exist, such as Pillai et al. (2022), their analysis focuses exclusively on the automotive industry, limiting cross-sector comparisons within manufacturing. There is a lack of studies that analyse different areas for potential AI application in the production processes of manufacturing companies and thus provide information on the current degree of dissemination and relevant fields of application. Furthermore, there is a lack of research that not only includes traditional adoption factors but also additional theoretical concepts such as the readiness of firms for AI, thus introducing further dimensions into the analysis of AI adoption.

2.2. AI readiness

A phenomenon closely related to analyses of technology adoption is an organisation's readiness for change, which is widely discussed at individual and organisational levels (Jones et al., 2005; Weiner, 2009; Rusly et al., 2012; Rafferty et al., 2013). Readiness for change refers to a shared psychological and practical state within an organisation in which members are both motivated to support change and confident in their collective ability to implement it. It is shaped by internal capacities and individual perceptions, which are influenced by how well the organisation communicates, involves its employees and promotes a sense of purpose and willingness (Jones et al., 2005; Lokuge et al., 2019). The theory of organisational readiness for change (e.g. Lokuge et al., 2019) is rooted in change management and provides the theoretical basis for our analysis of an organisation's readiness for AI (Hussain and Papastathopoulos, 2022). Literature confirms that a higher readiness of organisations for change favours the adoption of innovations (Weiner, 2009; Kelly et al., 2017; Antony et al., 2023). A strong readiness for change within a firm gives organisations the flexibility to reconfigure their resources (Hussain and Papastathopoulos, 2022). This is why we turn to the theoretical foundations of the Resource Based View (RBV) including the organisational capabilities framework in the field of strategic management literature (Barney, 1991; Grant, 1991; Amit and Schoemaker, 1993; McGrath et al., 1995; Bharadwaj, 2000). This theoretical perspective offers valuable insights into how companies cultivate and orchestrate the distinct resources and capabilities essential for gaining a competitive edge in the AI era (Schryen, 2013; Mikalef and Gupta, 2021; Peretz-Andersson et al., 2024).

The core tenet of the RBV revolves around the strategic importance of firm-level resources (Barney, 1991). According to the RBV, competitive advantage arises from effectively harnessing unique resources, providing a nuanced understanding of these assets (Priem and Butler, 2001). Grant's framework (1991) discerns various types of resources, categorizing them into tangible, intangible, and personnel-based categories. In addition to resources, the RBV introduces organisational capabilities as a combination and orchestration of resources, resulting in a company's ability to seamlessly integrate and deploy other resources to attain a competitive advantage (Amit and Schoemaker, 1993). These functional capabilities can be amalgamated to form cross-functional capabilities, further enhancing a firm's competitive positioning (McGrath et al., 1995).

Recent literature in the information systems field extends the RBV framework to elucidate how information technology (IT)-related resources can be harnessed to create IT capabilities, which, in turn, impacts competitive performance (Schryen, 2013). IT capabilities manifest themselves in various forms, including social media capabilities, business analytics, and big data capabilities (Gupta and George, 2016). Recent research underscores the pivotal role of AI capabilities in driving performance improvements through AI-powered solutions, which Mikalef and Gupta (2021, p. 2) define as '[…] the ability of a company to select, orchestrate, and leverage its AI-specific resources'. To maximise the benefits of AI, organisations need to cultivate a unique combination of tangible, intangible, and human AI-specific resources (Mikalef and Gupta, 2021; Horvat et al., 2023).

Incorporating the RBV logic allows us to comprehend the fundamental principles of resource-based readiness for AI technology. Within this framework, AI-specific tangible and intangible resources assume central roles in developing AI capabilities and shaping the success of AI adoption (Horvat et al., 2023). Tangible resources encompass the requisite IT infrastructure for AI applications, including e.g. hardware for data storage and processing and software for intricate data processing (Gupta and George, 2016; Mikalef and Gupta, 2021). The importance of data in AI, with its diverse types and voluminous nature, underscores its pivotal role as one of the most challenging aspects of AI implementation. In contrast, intangible resources are marked by their uniqueness and heterogeneity, stemming from organisational history, personnel, processes, and contextual factors (Grant, 1991; Sirmon et al., 2011). Research on AI readiness underscores the paramount importance of intangible resources in both the adoption and performance enhancement (Alsheibani et al., 2019; Jöhnk et al., 2021; Horvat and Heimberger, 2022). Finally, human resources, encompassing the collective knowledge and skills of employees, are vital components of AI readiness (Alsheibani et al., 2018; Horvat and Heimberger, 2022). These resources entail technical IT skills essential for introducing and applying IT solutions, as well as managerial IT skills that involve conceptualising, creating, and utilising IT applications to enhance various aspects of a business. These skills are cultivated over time and are often specific to each organisation (Heimberger et al., 2023).

Understanding the interplay of tangible and intangible resources, along with the critical role of human resources, is paramount for AI readiness (Horvat and Heimberger, 2022; Heimberger et al., 2023). We assume that companies can achieve individual levels of readiness, which in turn provides information about the current state (regarding AI readiness) of the organisation (Hussain and Papastathopoulos, 2022). The development of resources along each of these resource based readiness levels form the basis for the successful adoption of AI.

2.3. Integrated research framework and hypothesis

While some articles have begun to examine the links between AI readiness and AI adoption, research in this area is still rare (Alsheibani et al., 2019; Jöhnk et al., 2021; Issa et al., 2022; Uren and Edwards, 2023). Analyses consider different factors and dimensions and lack broad empirical validation of the relationship between readiness and adoption. However, research agrees on a complex interplay between adoption and readiness, with readiness being an important prerequisite for successful AI adoption throughout the entire adoption process (Jöhnk et al., 2021; Uren and Edwards, 2023).

In line with these perspectives, we build on the theoretical foundations of organisational readiness for change and the foundations of technology adoption. Regarding AI readiness, we consider an organisation's internal AI-specific resources that provide information about a company's AI readiness. We categorise these resources into technological and organisational AI readiness. We then link the construct of AI readiness to AI adoption and assume a direct and significant influence of AI readiness on successful AI adoption. We thus assume that there is a relationship between different dimensions of AI readiness, defined by critical AI-specific resources that an organisation can develop and configure, and the actual introduction of AI in the production system (see Fig. 1).

Readiness observations usually include specific factors based on adoption theories or processes (e.g., by Jöhnk et al. (2021) or Aboelmaged (2014)). Analyses of readiness for AI typically involve the analysis of specific factors within dimensions, such as an organisational dimension (Jöhnk et al., 2021), a technical dimension (Lerch et al., 2022; Heimberger et al., 2023), or a combined view of several fields (Uren and Edwards, 2023; Heimberger et al., 2024). Within those dimensions, readiness approaches are recognised as an important component when considering innovation, as they can uncover factors that prevent companies from adopting AI or influence them positively (Uren and Edwards, 2023). A large number of factors influence the adoption of AI in the production processes of manufacturing firms (Heimberger et al., 2024), however, we need to limit the factors considered in our analysis. It is our intention to consider all high impact factors influencing AI adoption while keeping the readiness model manageable to be able to enable group comparisons and provide decision makers with suggestions for action. We searched the literature analysing AI readiness and AI adoption (Jöhnk et al., 2021; Lerch et al., 2021; Horvat and Heimberger, 2022; Heimberger et al., 2023, 2024; Uren and Edwards, 2023) for the

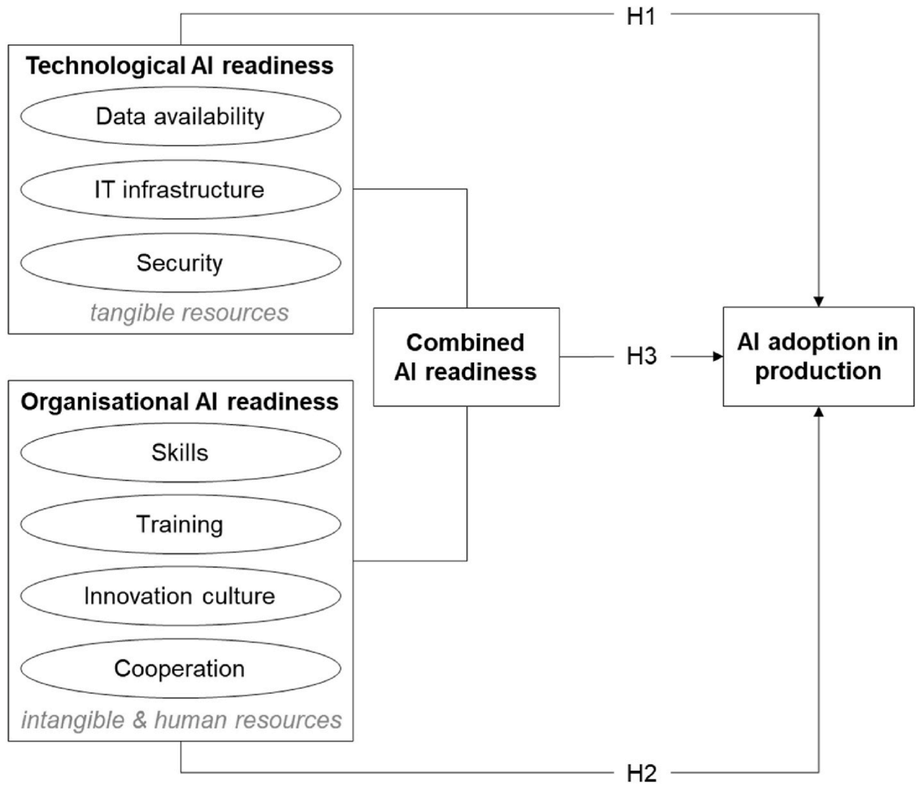

Fig. 1. Conceptual framework of AI readiness and AI adoption analysis in production.

most important factors following the RBV in the realm of tangible resources, human resources and intangible resources. After collecting and structuring the factors derived from the literature, we were able to identify seven factors that appear to be of particular importance for AI in a production context. We then categorised the factors derived into two dimensions forming our AI readiness model. Each factor can be categorised into different levels of readiness, allowing the current status of the company to be assessed based on the intensity of deployment.

Building on the principles of RBV and following key adoption analyses based on the TOE framework, we assess a company's AI readiness based on two dimensions: technological AI readiness (comprising tangible resources) and organisational AI readiness (including intangible as well as human resources). The resource-based factors of each dimension focus on the internal factors of the organisation. We refrain from including external factors (e.g. laws, regulations or the economic situation) in our AI readiness analysis in order to focus clearly on the internal readiness of an organisation, which it can influence and develop itself. In each dimension, several factors exert influence on the company's AI readiness, comprising three factors in the technological dimension and four in the organisational dimension. Drawing on recent studies, we include data availability and IT infrastructure as fundamental technical prerequisites for AI implementation on the technological side, alongside the need to ensure security within the production context. On the organisational side, we analyse the prevailing skills and training initiatives in order to successfully implement AI. In addition, we analyse the culture of the workforce as well as the willingness to cooperate (both within and outside of companies), which also influence the introduction of AI (Heimberger et al., 2024). We describe all factors in detail in the following section.

Companies have the opportunity to shape their resource based AI readiness by implementing relevant measures and fostering them internally, which emphasises the importance of including these two dimensions in the readiness analysis. We stress that technological and organisational AI readiness separately, as analysed by Heimberger et al. (2023), Lerch et al. (2022), or Jöhnk et al. (2021), as well as the combined AI readiness of both dimensions influence whether a company adopts AI in the production context. We assume that companies can only successfully adopt AI if they have established AI-related resources and thus a fundamental AI readiness. These considerations lead to three hypotheses, which are derived in the following sections and the conceptual framework visualised in Fig. 1.

2.3.1. Effects of technological AI readiness

The foundation of digital transformation is data, which is generated by a multitude of sensors in a smart and digitised factory (Roblek et al., 2016; Oliveira et al., 2020). Since input data is a prerequisite for AI for self-improvement and learning, companies that want to use AI efficiently must ensure the availability of data (Hartley and Sawaya, 2019; Dubey et al., 2020). When integrating AI into existing systems, processes and programs are often supported with algorithms designed to improve their performance (Mantravadi et al., 2019). Consequently, existing systems play a crucial role in digitizing workflows, generating data and potential AI integration.

Building a robust AI infrastructure for both present and future systems requires the availability of IT resources (Chiang et al., 2022). This includes investments in the infrastructure as well as capabilities necessary for data analytics (Wuest et al., 2020). In production organisations, IT departments are responsible for providing the necessary infrastructure into which intelligent technologies can be integrated and which form the basis for the generation of numerous data in the sense of the Internet of Things. The foundation of IT capability (Garrison et al., 2015; Awamleh and Bustami, 2022) is seen as a key driver in addressing complex challenges and enabling the IT department to implement AI technology swiftly and efficiently (Ghani et al., 2022).

Due to production facilities, which are often data-driven, production companies and their IT systems are vulnerable to failures as well as cyberattacks, which can reduce their competitiveness (Turner et al., 2019; Azambuja et al., 2023). Next to general data protection issues, safety risks are the subject of discussion in connection with AI (McCauley, 2007; Trakadas et al., 2020). These conditions indicate that companies must implement measures to ensure the security of operational data, teach employees and thus create a fundamental basis for secure systems in production (Trakadas et al., 2020; Akinsolu, 2022).

In view of the necessity of IT infrastructure and the availability and security of data for the successful adoption of AI, we assume that these technological AI resources within the organisation form an important basis for the adoption of AI in a production context. The availability of these resources together forms a specific technological AI readiness of a firm. Therefore, we assume:

H1: A higher level of technological AI readiness in manufacturing companies is positively associated with an increased likelihood of AI adoption in production processes.

2.3.2. Effects of organisational AI readiness

In order to exploit the potential of AI, the workforce within the manufacturing firm must possess a variety of digital skills, which include technical, cognitive as well as social skills (Drobot, 2020; Trakadas et al., 2020; Kinkel et al., 2022). Although production companies may choose not to develop smart algorithms themselves, they must ensure basic technical skills and competencies in the use of the technology, such as the general digital affinity and process understanding of production employees in order to enable digital transformation (Ghobakhloo and Ching, 2019; Hartley and Sawaya, 2019).

To ensure a profound skillset amongst the production workforce, organisations must prepare their employees in a variety of areas to adapt to new technologies, improve their skills, and create a deeper understanding and, consequently, gain greater acceptance of these advances (Drobot, 2020; Mubarok and Arriaga, 2020; Sharma et al., 2022). Addressing this need for appropriate training requires resources and investments to improve workforce capabilities (Ghobakhloo and Ching, 2019; Boavida and Candeias, 2021; Kyvik Nordås and Klügl, 2021; Vernim et al., 2022).

Innovative corporate cultures are characterised by continuous improvement (Bettoni et al., 2021), productivity (Kyvik Nordås and Klügl, 2021), innovativeness (Olsowski et al., 2022) as well as risk-taking (Dubey et al., 2020), which increases companies' ability to adapt to ever-changing market conditions and make appropriate decisions (Dubey et al., 2020; Boavida and Candeias, 2021; Bonnard et al., 2021; Tariq et al., 2021). An 'AI-ready culture' (Chiang et al., 2022), characterised by digital readiness, data integration, continuous development, and awareness of integrating smart technologies, can be supportive in the adoption of AI. Organisations that develop an environment for openness and new perspectives enable more opportunities for awareness and innovative approaches can emerge (Zmud, 1982).

AI adoption can also be positively influenced by collaborations (both internal and external to the organisation) (Drobot, 2020; Trakadas et al., 2020; Akinsolu, 2022) as knowledge sharing and exchange can facilitate adoption (Drobot, 2020; Boavida and Candeias, 2021). External IT expertise is usually required to integrate AI into existing production processes, including, for example, implementation processes and organisational restructuring (Olsowski et al., 2022). Firms may benefit from public-private collaborations, e.g. with universities, and may gain access to government funding. In such research collaborations, ideas can be easily developed, tested and implemented in a collaborative environment among different actors (Ghani et al., 2022; Williams et al., 2022).

The development of organisational AI resources within the company, including skills, training, a culture of innovation and cooperation, forms an important foundation for a company's organisational readiness for AI in production. We therefore assume that:

H2: A higher level of organisational AI readiness in manufacturing companies is positively associated with an increased likelihood of AI adoption in production processes.

2.3.3. Effects of combined AI readiness

Having isolated the technological and organisational dimensions of AI readiness, our analysis takes a significant step forward by incorporating a synthesis of both aspects in our third hypothesis. Based on insights from the RBV-based AI literature(Mikalef and Gupta, 2021; Horvat et al., 2023), companies take different paths to prepare for AI integration, with a choice between a focus on organisational (intangible) measures or on technological (tangible) advances. Some companies initially focus on strengthening their organisational resources, thus creating a solid structural foundation, while others prioritise technological capabilities and gradually build tangible resources (Horvat et al., 2023). Despite these different paths, each of them can culminate in the adoption of AI in a production context and lead to complex resource combinations. In recognition of the distinct but equally critical role that both dimensions play in driving successful AI adoption, we introduce a unified AI readiness concept into our research framework.

This approach combines factors from both dimensions and summarises them in a consolidated index. Our integrated model is based on the principles of relative value theory and assumes that it is important to build both technological and organisational AI-related resources in order to implement AI. We hypothesise:

H3: A higher level of combined AI readiness in manufacturing companies is positively associated with an increased likelihood of AI adoption in production processes. This influence on AI adoption is stronger than in the assumed relationships in H1 or H2.

3. Data and methodology

The empirical data used in this study were drawn from the *German Manufacturing Survey* (GMS) 2022. This survey was first launched in 1993 (Lay and Maloca, 2004) to systematically observe production companies regarding their product, process, service and organisational innovations, it is currently conducted every three years, and has been part of the *European Manufacturing Survey* since 2001 (Fraunhofer Institute for Systems and Innovation Research ISI, 2024). The data from this broad multi-topic survey were used in several firm-level studies (e.g. Bikfalvi et al. (2013); Bikfalvi et al. (2014); Dachs and Zahradnik (2022); Kinkel et al. (2011); Kirner et al. (2015)). The authors belong to the scientific team responsible for its operationalisation and questionnaire development for Germany.

We chose the German manufacturing sector for our analysis because Germany was an early lead market for the digitalisation of industrial production (Kagermann, 2015) and is a large economy whose industrial applications are highly competitive and considered a role model for other industries worldwide (Audretsch et al., 2018; European Commission, 2024). Furthermore, the year 2022 is a very interesting point in time to analyse the dissemination of AI applications in manufacturing, as it captures the diffusion of industrial applications based on speech recognition, image processing or computer vision after 2012 (Escobar et al., 2020; Fahle et al., 2020) and the boost by COVID-19 (Kapoor et al., 2021).

3.1. Data base and sample description

GMS addresses manufacturing firms with 20 or more employees from all manufacturing sectors (NACE Rev. 2, 10–33) in Germany. The questionnaires are sent to firms with at least 20 employees from all areas of manufacturing (NACE Rev. 2, 10–33) and are completed by production managers, chief technology officers, or general managers of the production facilities. The data for this study is based on the most recent survey, GMS 2022, which has been conducted as a push-to-web survey between fall 2021 and spring 2022 (Jäger and Maloca, 2022). This survey addressed a random gross sample of 15,299 manufacturing firms with at least 20 employees in Germany, which was drawn from a firm database as a proportionally stratified random sample in line with the distribution in the population. However, 2047 selected cases turned out to not be part of the target population, or to be not active anymore. The processing of the random sample was carried out according to a strict protocol.

A total of 1334 companies returned useable responses that met the quality criteria of more than 75 % of answered questions. This corresponds to a response rate of 10 % in relation to the net sample for the GMS 2022. Moreover, the realised data is a representative image of the manufacturing industry in Germany as the regional distribution, size classes and industry structure are in line with the distribution in the data from the Federal Statistical Office (Jäger and Maloca, 2022).

GMS 2022 provides a large set of data, including information on innovative production technologies and digitalisation, organisational practices and the implementation of training measures as well as performance indicators and general company data. Questions essentially comprise verifiable facts and figures, hardly any personal assessments are captured. The items on the use of AI in production processes were specifically developed for the 2022 survey to cover the production specific use of AI in linkage to their production context by a cross-country team including the authors. These data enable us to examine the relationship between AI readiness and AI adoption in manufacturing firms.

For the following descriptive statistics, bivariate group comparisons and multiple logistic regression analyses on the interlinkage between AI readiness and AI adoption, we use an extract of the GMS 2022 data from 1130 firms. This extract includes all cases for which the necessary information regarding AI readiness, AI adoption and firm and production characteristics was provided. The comparison between the analysed data set and the excluded cases shows that the assumption of a systematic bias in the characteristics used can be rejected. Table 3 in the appendix summarises information on the main characteristics of the analysed data and provides the comparative data of the population regarding firm size and sector as provided by the Federal Statistical Office.

3.2. Measures

3.2.1. Dependent variables: AI adoption

The measure of AI adoption in production used in the following analyses captures the fact of the use AI in manufacturing processes and thus focuses on successful implementation of AI. It is based on companies' responses regarding their use of software solutions in specific production areas. Firms were asked to indicate in which production area a specific software is used. In a follow-up question, respondents were further asked whether these software solutions incorporate self-learning functionalities, explained in the questionnaire as algorithms capable of automatically improving their performance by recognizing patterns or irregularities without being explicitly programmed for each case (Toorajipour et al., 2021; Lerch et al., 2022; Merhi and Harfouche, 2024). We intentionally refrain from differentiating between specific AI technologies (e.g., machine learning, deep learning, or expert systems) and instead focus on the general presence of AI functionalities within production-related applications. This approach accounts for the fact that the respondents, typically not IT specialists but managers with operational responsibilities, may lack the technical expertise to accurately identify the underlying AI methods employed. Accordingly, the survey did not inquire about the specific types of AI technologies or models used. Rather, our focus lies in identifying whether self-learning functionalities, as a defining feature of AI, are present in the software systems used in production contexts, independent of their technical implementation.

Within this research, we consider four application areas commonly associated with AI-driven production processes (Fahle et al., 2020; Javaid et al., 2021): (1) AI-based software solutions for managing production processes (e.g., process monitoring), (2) for quality control (e.g., defect detection), (3) for maintaining machinery and equipment (e.g., condition monitoring), and (4) for managing internal logistics (e.g., warehouse management, transportation). These domains were chosen to reflect the integration of learning-based AI technologies in the production context. Thereby, the aim of operationalisation was to determine whether companies are using AI at all in these areas, rather than to what extent. Therefore, GMS asked a yes/no question about AI implementation for each of these areas of application.

In the here presented analyses, we focus on firms that use AI for production processes. The indicator therefore distinguishes between firms that already use an AI application in at least one of the four areas of their production (AI adopter) and those that do not yet use any software with self-learning functionality in one of these four AI applications applied (non-AI adopter). As done in previous studies of AI adoption, we thus treat our dependent indicator of AI adoption as a dichotomous variable (Dahlke et al., 2024; Zhan et al., 2024).

3.2.2. Independent variables: AI readiness indices

Our conceptual framework considers both the technological and organisational perspectives of AI readiness, as these are the two dimensions that encompass the tangibles and intangibles of a company, which can be influenced by the organisation itself. In our analyses, we use separate indices for both dimensions as well as a combined index to capture the interaction between the two individual AI readiness dimensions. Each readiness dimension of the indices consists of different factors, which are measure by different survey responses and which, in their various configurations, lead to varying readiness assessments for each dimension. The combined AI readiness index, in turn, connects the two dimensions. In the following paragraphs, the indices are explained in more detail and the operationalisation is outlined; the constitutive factors are additionally listed in Table 1 as well as the measures they are based on. Moreover, in the appendix, the distributions of the constitutive factors for the three constructs in German manufacturing are displayed (see Table 4 in appendix).

While many of the factors in these indices may primarily reflect broader aspects of digitalisation rather than AI-specific technologies, we assume that these fundamentals are necessary for the successful implementation of AI and therefore reflect a readiness for AI. Technological AI includes important foundations of data availability, IT infrastructure, and security, while organisational AI readiness addresses the importance of skills, training, innovation culture, and cooperation. These components are essential for the successful adoption of AI, as a sufficient digital infrastructure and organisational capacity are prerequisites for effective AI implementation (Jöhnk et al., 2021; Uren and Edwards, 2023). Thus, while the indices do not measure existing AI algorithms or specific AI-related technologies, they capture critical AI-related resources and measure enablers for a successful AI integration in production contexts.

On the one hand, the *technological AI readiness index* is operationalised as an index based on the measurement of the three factors presented above (Fig. 1) using seven indicators. Each factor is measured on an ordinal scale ranging from zero to two, the distribution in the manufacturing sector is shown in Table 4 in the appendix. Zero points are achieved if none of the production systems are in use, no employees are assigned to IT and no measures are implemented to safeguard operational data. One point, meaning basic technological AI readiness is achieved if one or two of the production systems are in use, <5 % of the employees are assigned to IT, and one or two of the security measures are implemented. The maximum score (two points) is achieved when at least three of the production systems are in use (data availability), a minimum of 5 % of the employees at the site are engaged in IT, and if at least three of the four operational data security measures have been implemented.

With the additive combination of these three factors, a maximum score of six points can be achieved. To measure technological AI readiness, this score was standardised to a range from zero to two and then transformed into an ordinal indicator with four levels: no tech AI readiness (0 points), low technological AI readiness ($(0<x \leq 2/3)$ points), medium technological AI readiness ($2/3<x \leq 4/3$), and high

Table 1
Operationalisation of AI readiness dimensions.

	Factor	Measurements	Measurement level
Technological AI readiness	Data availability	*Use of data-based technologies in production*	
		– use of software systems for production planning and control (e.g. ERP system)	yes/no dummy
		– digital data exchange with suppliers or customers (EDI)	yes/no dummy
		– use of product lifecycle or product process data management systems	yes/no dummy
		– use of near real-time production control systems	yes/no dummy
	IT infrastructure	*Professional specialisation*	share of total employees
		– share of operating personnel in IT infrastructure (hardware and software)	
	Data security	*Implementation of data security measures*	
		– measures raising the data security awareness of employees	yes/no dummy
		– use of special software solutions (e.g. controlled data use, access, etc.)	yes/no dummy
		– use of special hardware solutions (e.g. Network separation etc.)	yes/no dummy
		– implementation of special organisational data security measures (e.g. access restrictions)	yes/no dummy
Organisational AI readiness	Skills	*Use of digital communication technologies*	
		– use of mobile/wireless devices for programming and operating plants and machines	yes/no dummy
		– use of digital solutions for work plans/ instructions or drawings at the workers' workplace	yes/no dummy
	Training	*Offers for continuing education and skills development for production employees*	
		– focused on a specific task (e.g. machine maintenance, workstation instructions)	yes/no dummy
		– to support the introduction and use of digital production technologies or digital assistance systems	yes/no dummy
		– focused on data security and data compliance	yes/no dummy
	Innovation culture	*Measures to motivate and involve production employees in innovation processes*	
		– planning, controlling or monitoring functions for workers (task integration)	yes/no dummy
		– involvement of workers in product or process development	yes/no dummy
		– rewards for outstanding performance in the production or innovation area	yes/no dummy
	Cooperation	*Research & Development cooperation*	
		– with suppliers or customers	yes/no dummy
		– with other companies (not suppliers or customers)	yes/no dummy
		– with research institutions/ universities	yes/no dummy

technological AI readiness ($4/3<x \leq 2$).

On the other hand, *organisational AI readiness* is operationalised as an index based on the measurement of four factors presented above (see Fig. 1) using 11 indicators (see Table 1). As with the technological index, each factor is measured as an ordinal indicator with values zero, one or two; the distribution in the manufacturing sector is shown in Table 4 in the appendix. Zero points are awarded to companies that have no digital skills, do not use any training measures, do not implement any of the three open innovation culture measures and do not engage in collaborations. One point is scored if one of the two digital communication tools is used, one of the three continuing education measures is offered to production employees, if one of the three innovation culture measures is utilised, and if collaboration is already underway. Two points are assigned if both digital communication tools are used and digital skills are therefore considered standard requirements in production if at least two of the three trainings are offered, if at least two of the three organisational measures are applied, and an integrative culture of innovation therefore is structurally supported and can thus provide impulses for innovation and new knowledge in the companies.

To measure organisational AI readiness, this score was standardised to a range from zero to two and then transformed into an ordinal indicator with four levels according to the same classification criteria: no organisational AI readiness (0 points), low organisational AI readiness ($0<x \leq 2/3$), medium organisational AI readiness ($2/3<x \leq 4/3$), high organisational AI readiness ($4/3<x \leq 2$).

Finally, we create the combined AI readiness index based on these two indices of technological AI readiness and organisational AI readiness, intending to reduce complexity and decrease measurement errors compared to using the two separate indicators (e.g. Kromrey et al. (2016)). Since the correlation between the two dimensions is of interest, the combined AI readiness index is an additive index, as shown in Fig. 2. Thus, both the technological and organisational dimensions contribute equally to the combined AI readiness index. This was ensured by standardising both AI readiness dimensions and suggests that both dimensions complement and compensate to some extent. However, an interaction that would justify a multiplicative index is not assumed.

For constructing the index of combined AI readiness, the values on both dimensions are added up. No further weighting is applied. At the end, the resulting score is transformed into an ordinal indicator with five levels: no combined AI readiness, low combined AI readiness, lower medium combined AI readiness, higher medium combined AI readiness and high combined AI readiness. The group of firms assigned to *no combined AI readiness* includes those companies that either lack AI readiness in both dimensions or achieve no AI readiness in one of the two and only low readiness in the other, and are therefore still at the

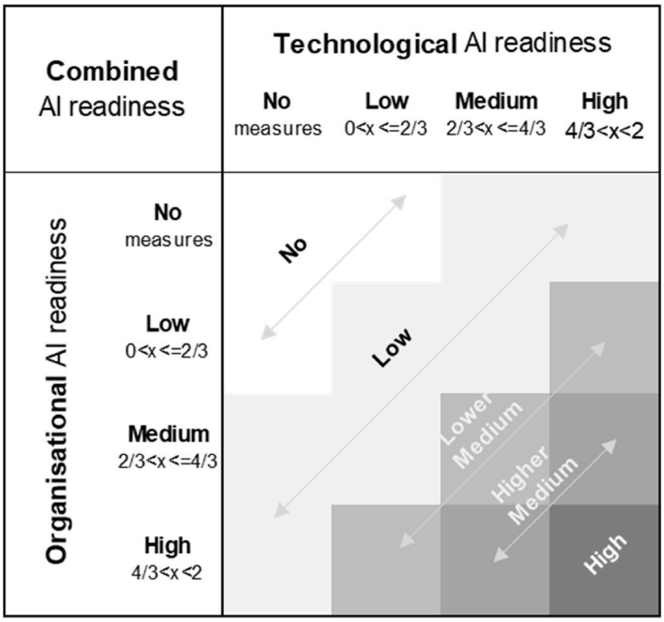

Fig. 2. Group assignment combined AI readiness.

very beginning. The *low combined AI readiness* group consists of the firms that rather focus on one dimension and mostly or completely ignore the other dimension. *Lower medium combined AI readiness* represents companies that are either at a medium readiness level in both dimensions or combine a high readiness in one with a low readiness on the other dimension. The group of *higher medium combined AI readiness* includes only those firms that combine a high readiness at one level with a medium readiness on the other one. Finally, the group of *high combined AI readiness* includes only those firms that have a high readiness rating for both technological AI readiness and organisational AI readiness. The group assignment is visualised in Fig. 3.

3.2.3. Control variables

In order to estimate the effect of AI readiness on AI adoption, structural characteristics of the firms and production characteristics are also taken into account in our analyses. As highlighted in previous research (DeStefano et al., 2022; Kinkel et al., 2022), we also assume that larger companies have more experience with the introduction of advanced production technologies and more opportunities and higher economies of scale to use AI systems efficiently in production. We also take into account the evidence from the literature that agile start-ups and small companies are among the pioneers in the AI adoption. Therefore, we take into account the firm size, measured as the number of employees, as a polynomial in the regression models (Kinkel et al., 2007; Armbruster et al., 2008; Broedner et al., 2009; Bikfalvi et al., 2013; Dachs et al., 2014). As a natural logarithm, the diminishing marginal utility of the number of employees is taken into account. With the simultaneous introduction of the quadratic term of this influence, we can also model a u-shaped relationship.

Considering the heterogeneity of manufacturing industries in terms of market and production-specific characteristics (e.g. automation, profit margin, digital environment) and the industrial differences with respect to AI adoption, we additionally control for the sector of a firm as adopted by other researchers analysing certain effects within the manufacturing industry (Armbruster et al., 2008; Broedner et al., 2009; Bikfalvi et al., 2013; Dachs et al., 2014; Rammer et al., 2022; Wang and Qiu, 2023). Based on open text information about the main product and perceived sector, firms are classified according to the sector classification NACE rev. 2 and grouped into eight classes afterwards.

As adopted in other studies (Kinkel et al., 2022, 2023), additional

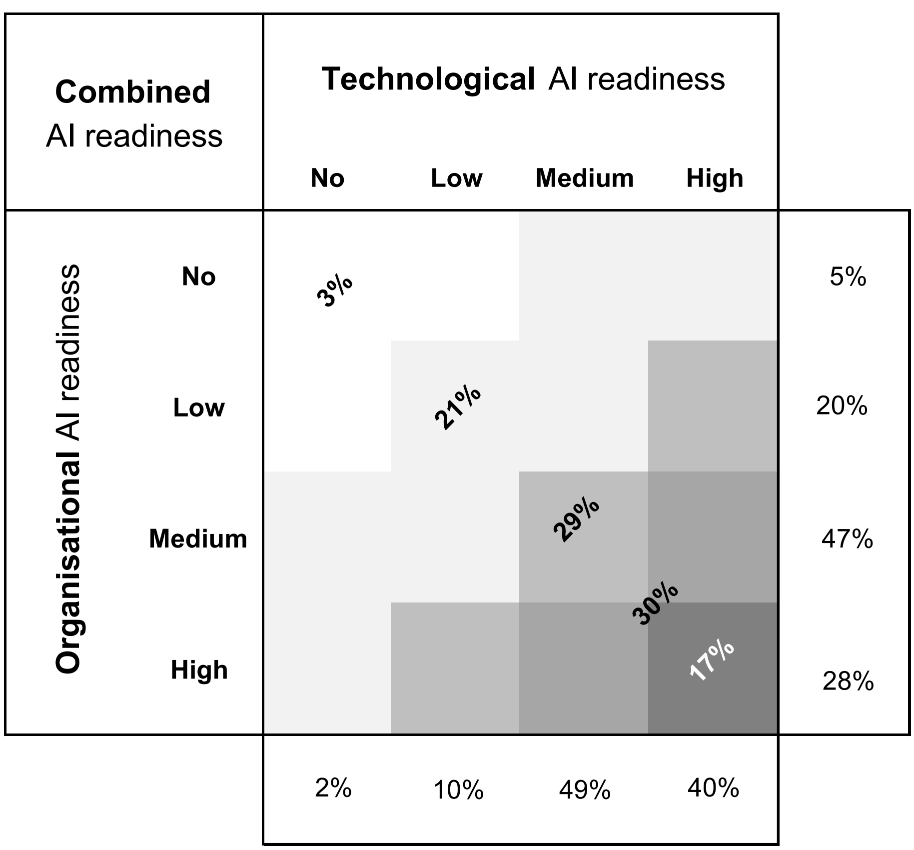

Fig. 3. Distribution of technological, organisational, and combined AI readiness.

control variables such as product complexity (simple products, medium complexity products, complex products), batch size (single lot, small/-medium lot, big lot) and the value chain position (manufacturer of final products, supplier, contract manufacturer) of the companies are suitable and have been interesting control variables in structural analyses of the manufacturing industry in regression analyses. We control for the batch size of the main production as we assume that companies with production processes in large batch sizes are more suitable for using AI solutions than companies with smaller batches or single unit production processes. Economies of scale are easier to realise under the frame conditions of large batch size production, enabling productivity growth through rationalising repetitive tasks (Broedner et al., 2009; Lay et al., 2010; Bikfalvi et al., 2013; Dachs et al., 2014). Product complexity is considered too as we assume that companies which produce simple products (in large volumes) have a higher need and more potential to automate their production processes than companies producing medium-complex or complex products (Broedner et al., 2009; Dachs et al., 2014). Finally, the value chain position is considered differentiating between manufacturers of final products for consumers or for industrial clients, system or parts suppliers, and contract manufacturers (Armbruster et al., 2008).

3.3. Model description and data analysis

To test our three hypotheses, we first conduct bivariate group comparisons to find out to which extent differences in AI adoption can be detected between the AI readiness levels of the three AI readiness indices. We apply Mann-Whitney U tests (Mann and Whitney, 1947) to compare two independent groups and the Kruskal-Wallis test (Kruskal and Wallis, 1952) for multi-group comparisons to check whether the differences between the respective AI readiness levels in H1, H2 and H3 can be due to chance or can be assumed statistically significant. The null hypothesis in each case is that there are no differences in the share of AI adopters between the different AI readiness levels.

As a second step, we conduct multiple regression analyses to test our hypotheses. Since the dependent variable in our three hypotheses is a dichotomous variable (0: no AI adoption; 1: at least one of the four AI applications in use), we estimate logistic regression models that allow us to control for other company characteristics in addition to AI readiness. The firm and production characteristics are included in the models as presented above. Initially, only the influences of these indicators are estimated for each hypothesis. The models are then expanded to include the respective AI readiness index (technological, organisational or combined AI readiness). We estimate the regression parameter, visualise the statistical significance for each model and report the model fit for the entire model.

In order to ensure the robustness of the estimates, *firstly* the collinearity of the independent influencing factors was tested. In advance, no higher correlations were found in the bivariate relationship; Spearman's rho did not exceed the value of .3 between the ordinal factors. Pearson's r2 is mostly also in this order of magnitude. Only the information on company size (logarithmised number of employees) and the AI readiness are correlated with $r = .434$ for the combined indicator and .334/.379 for organisational and technological AI readiness. In conclusion, besides firm size no relevant bivariate correlation was found. We will use split data analyses to examine possible differences in the estimates for different company size groups. *Secondly*, approximate VIF inflation factors were calculated for all regressions; with values mainly below 3 and all below 4, these were all below a critical limit. *Finally*, standardised residuals of the regression estimations below 3 did not indicate specific outliers, nor did the analyses of the cook's distance with values below .36 reveal concerns on this behalf. Thus, additionally considering the specific model fit parameters, reliable logistic regression estimates can be assumed.

4. Results

4.1. AI readiness in manufacturing companies

Firstly, there are intriguing findings concerning AI readiness in the manufacturing industry (refer to Fig. 3). On one hand, in terms of resources related to technological AI readiness, the majority of analysed companies fall into the category of medium (49 %) or high (40 %) readiness. This suggests that a solid technological foundation for integrating AI applications into production contexts has been established in the manufacturing industry, irrespective of actual AI usage. On the other hand, in contrast to technological readiness, a high level of organisational readiness for AI is less frequently achieved (28 %). Interestingly, one in four manufacturers exhibit no (5 % of all companies) or only low (20 %) level of resources related to organisational AI readiness. Overall, when analysing these two dimensions of AI readiness separately, it becomes apparent that manufacturing companies are more prepared in terms of technological readiness than in organisational readiness.

When considering both AI readiness dimensions together, the findings reveal notable distinctions (see Fig. 3). Roughly a quarter of all firms either show no readiness (3 %) or are at a low level (21 %) in terms of combined AI readiness. Medium combined AI readiness is prevalent among manufacturers, with approximately 60 % of companies falling into this category. Only about one-sixth of firms (17 %) demonstrate high combined AI readiness. It is interesting to note that the proportion of firms with high AI readiness is significantly lower when considering combined AI readiness compared to the separate dimensions. These results underscore the significance of not only considering AI readiness as a combined score but also opening it as a 'black box' and examining its two dimensions as distinct groups of related resources.

Further examinations highlight significant differences between firms of different size classes (see Fig. 4). While the vast majority of large companies with more than 500 employees have a high level of technological AI readiness, less than 60 % of these companies exhibit a high level of organisational AI readiness. In small companies, just under a quarter achieve the highest level of technological readiness, and less than a fifth are organisationally prepared at the highest level.

Not surprisingly, large companies also have a clear lead in terms of combined AI readiness (see Table 5 in appendix). However, the reality is different already for medium-sized companies. Only a quarter achieve the highest level of combined AI readiness. Among small companies with fewer than 50 employees, this figure drops to 6 %. It's noteworthy that among companies with fewer than 100 employees, still a quarter to a third exhibit either no readiness or only low AI readiness, a share significantly lower than the less than 10 % among larger companies. Moreover, bivariate analyses reveal significant variance in combined AI readiness depending on industry affiliation as well as production characteristics. Manufacturers producing complex products and produce in larger series tend to have a higher combined AI readiness, as do system and parts suppliers.

4.2. AI adoption in production

Secondly, the data is also highly informative regarding the implementation of AI solutions in production (see Fig. 5). While 8 % of manufacturing firms in Germany use AI in software tools for production management, 7 % leverage AI for quality control and 6 % for both internal logistics management and machine maintenance. Overall, 14 % of German manufacturing companies implement AI in at least one of the four production-specific application areas examined. Thus, we can conclude that the adoption of AI in production is not yet widespread. As of 2022, AI had not become a standard application in manufacturing in Germany. Moreover, the selected application areas appear to be quite specific, with none of the four areas of AI support standing out prominently. Furthermore, companies that do employ AI often utilise it in only one or, at most, two application areas.

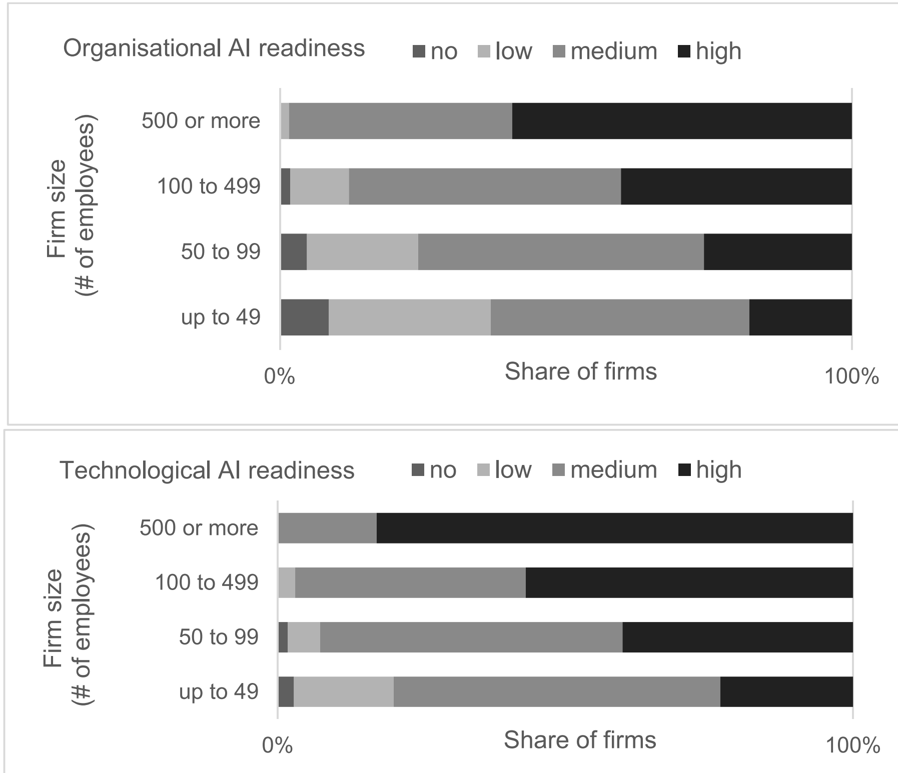

Fig. 4. Technological and organisational AI readiness for different firm size groups.

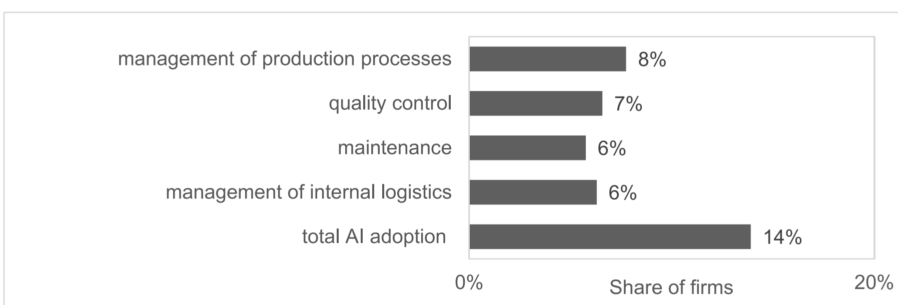

Fig. 5. AI adoption per application area in production.

There are clear structural differences in the spread of AI (see Table 5 in the appendix). As expected, large companies with more than 500 employees use AI in production much more frequently than companies with fewer employees. In terms of sector, the automotive industry stands out by far. In this sector, almost a third of companies use an AI application in production. The adoption rate of the other sectors differs significantly less, with the exception of the very low rate in the chemical and pharmaceutical industry. There are also clear differences regarding product complexity. 20 % of manufacturers of complex products use AI in production compared to 8 % of manufacturers of simple products. The differences are smaller regarding batch size and no clear trend can be observed in terms of position in the value chain.

4.3. *Linking AI readiness and AI adoption*

To analyse the relationship between AI readiness and adoption in manufacturing companies, we conducted regression analyses. Table 2 presents the results of three regression model estimations, each for the impact of technological AI readiness, organisational AI readiness and combined AI readiness on the odds of a company being an AI adopter. The three estimated models are statistically significant. The highest explanatory power is reached using the combined AI readiness according to the lowest Log-Likelihood measure.

Looking at the estimation for H1 on the connection between the level of resources related to technological AI readiness and AI adoption, the results of our model, firstly, reveal the significant role of some structural characteristics of the companies that influence the odds of AI adoption and which thus emerge as key drivers of AI adoption. The results underline the role of the industry ($p < 0.05$) and the product complexity ($p < 0.01$) as decisive factors in the adoption of AI. AI adoption is more likely for medium (factor 1.75) and particularly for high product complexity (factor 3.37) than for companies with simple products. In comparison to the machinery sector, AI adoption is among rubber and plastics producers 2.5 times more likely resp. in the automotive industry the odds are 3 times higher. Batch size and the position of the companies in the value chain seem to not contribute to the model. Finally, for the relation to the firm size a u-shaped relationship is supported as both indicators reveal a statistically significant role and contribute together to the model.

However, when considering the overall impact of the level of

Table 2
Results of the logistic regression model estimations on AI adoption in production.

Variables	Model H1 Technological AI readiness OR/Sig.	Model H2 Organisational AI readiness OR/Sig.	Model H3 Combined AI readiness OR/Sig.
Firm/production characteristics			
Firm size	**	**	**
# of employees (Log value)	0,45**	0,48*	0,43**
Squared log value	1,09**	1,08**	1,09**
Sector (Reference: Machinery)	**	**	**
Metal industry	1,76*	1,82*	1,82*
Food and beverage industry	1,95*	2,20*	2,17*
Chemical and pharmaceutical	0,68	0,65	0,66
Rubber and plastics industry	2,55***	2,44***	2,48***
Electrical/ electronics industry	0,96	0,93	0,93
Automotive industry	3,19***	2,98***	3,02***
Others	1,67	1,67	1,64
Product complexity (Reference: simple)	***	***	***
Medium complex	1,75**	1,71*	1,69*
High complex	3,37***	3,20***	3,04***
Batch size (Reference: single lot)			
small/medium lot	1,30	1,30	1,24
big lot	1,77*	1,82*	1,69
Value chain position			
Supplier (system-, part-)	1,20	1,21	1,20
AI readiness			
Technological AI readiness (Ref. low)	*		
no	0,60		
medium	1,22		
high	1,99*		
Organisational AI readiness (Ref. low)		**	
no		0,98	
medium		1,33	
high		2,11**	
Combined AI readiness (Ref. low)			***
no			1,65
low medium			1,28
high medium			1,99**
high			3,04***
Constant	0,139*	0,12**	0,16*
Model fit			
Log Likelihood/sig.	840,73***	840,05***	834,25***
Cox & Snell R^2	0,06	0,06	0,07
Nagelkerke R^2	0,11	0,11	0,12
Explanatory contribution of the AI construct (delta Log Likelihood)	7,81*	8,49**	14,29***

n = 1130.
Significance levels: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

resources related to technological AI readiness on AI adoption, the results do not show a statistically significant contribution; the estimation only reveals a contribution at a 10 % significance level. Therefore, we must reject H1. However, the estimated odds ratios confirm the expected relationship of an increasing likelihood of AI adoption with higher technological AI readiness.

The results for H2 on the link between the level of resources related to organisational AI readiness and AI adoption also support the significance of some structural conditions of the firms. Again, a statistically significant impact of the industry affiliation, the firm size and the product complexity on AI adoption is estimated. Moreover, the findings demonstrate a statistically significant correlation between the level of resources related to organisational AI readiness of a firm and AI adoption in production ($p < 0.05$), even with these structural factors controlled for. Thus, the results support the expected positive link between organisational AI readiness and AI adoption. AI adoption is two times more likely with a high organisational AI readiness than with a low organisational AI readiness. The estimation also still shows a positive influence for the mean level of organisational AI readiness with a factor of 1.13 resp. revealed a negative factor for no organisational AI readiness, even though these estimates are not statistically significant in itself. Due to the statistical significant impact of the construct for the model and the estimated factors, we can uphold H2.

The results of the third regression model estimations (H3) also support the statistically significant correlation between various structural characteristics of the companies and AI adoption. Here too, firm size, sector affiliation and product complexity make a statistically significant explanatory contribution to the model. Again, the batch size and the position in the value chain have no statistically significant contribution to the model. The addition of combined AI readiness clearly improves the estimated model ($p < 0.01$). AI adoption is three times more likely for firms with a high combined AI readiness than for firms with low combined AI readiness. Firms with a higher medium combined AI readiness still have a significant advantage. The odds for having implemented an AI solution in production is two times higher than for firms with a low combined AI readiness. Based on these results, we can uphold H3.

Besides this central finding, we highlight some further details in our empirical analysis. The estimated results already show that, in terms of AI readiness, the differentiation between high AI readiness and high medium readiness is of importance. In contrast, the differentiation of the lower levels does not provide any insights with regard to AI adoption. Fig. 6 displays the calculated probabilities of AI adoption for a typical case of a mechanical engineering firm with a single unit production for producing a finished product. The distance for the lines of the various AI readiness levels visualise this central finding. Moreover, Fig. 6 also illustrates the u-shaped relationship between firm size and AI adoption. When controlling for sector affiliation, batch size, product complexity and AI readiness, the probability of using AI for larger firms is much higher than for medium sized firms, whereas very small firms also seem to have a higher probability than medium sized firms. This relation becomes especially relevant for producers of complex products. With medium complex production smaller firms seem not positively differ from medium sized firms.

However, as firm size and AI readiness are quite correlated, the regression analyses were repeated separately for small firms with less than 50 employees, for smaller firms with less than 100 employees, and for larger firms with at least 100 employees. The estimated results reveal a quite different picture for smaller firms (see Table 7 in appendix) in contrast to larger firms (see Table 8 in appendix). The tables in the appendix summarise the estimated results at construct level. It is shown whether a construct contributes statistically significantly to the estimation. According to these results, the odds for an AI adoption by smaller firms is affected by the complexity of the produced product as well as the organisational or combined AI readiness level. However, neither the sector affiliation nor the firm size have a relevant impact. The overall explanatory power of these models is rather low. In contrast, the models estimated for larger firms only reveal quite the contrary. The chance of AI adoption is strongly influenced by firm size and sector affiliation. Additionally, the product complexity contributes to the estimation as well. However, the AI readiness level does not affect the estimation. The overall explanatory power of these models is quite high in comparison. To verify these new insights, we also tried to model an interaction between firm size and AI readiness. However, we could not find a fitting relationship. Further research needs to be conducted on this behalf.

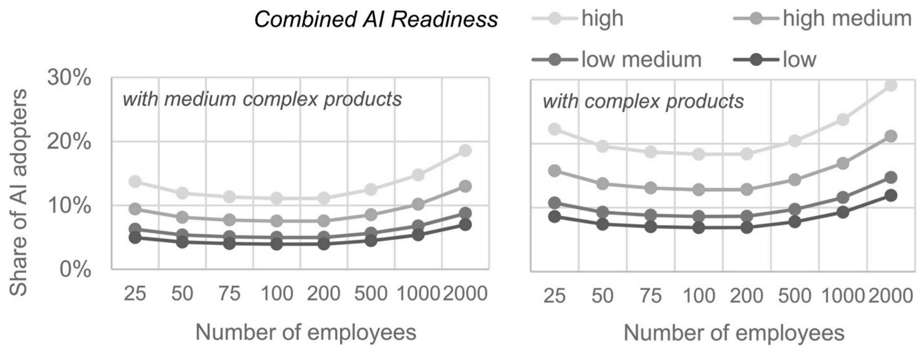

Fig. 6. The estimated share of AI adoption among firms of the machinery sector depending of the product complexity and firm size
Note: Estimated probabilities of AI adoption by average producers of machinery with single unit production producing finished products showing different levels of AI readiness and product complexity.

5. Discussion

Recent studies have shed light on AI adoption from different perspectives (Steininger et al., 2022). Today, we see AI readiness as a combination of various resources companies must have to be able to implement an AI solution (Alsheibani et al., 2018; Jöhnk et al., 2021; Horvat and Heimberger, 2022; Heimberger et al., 2023). We also know how companies deal with the orchestration of these resources from a process perspective (Peretz-Andersson et al., 2024). Moreover, we know about the main factors important for the adoption of AI solutions in manufacturing companies (Kinkel et al., 2022; Heimberger et al., 2024). What remains under-explored in the recent literature is the relationship between AI readiness, understood as the achieved combination of relevant resources, and the actual adoption of AI solutions in manufacturing companies (Dwivedi et al., 2021; Steininger et al., 2022). It is therefore still unclear which specific types of resources and their combinations are most important for the successful introduction of AI solutions and how manufacturing firms can prepare themselves for the introduction of AI in terms of available resources. This paper addresses this research gap by empirically examining how AI-specific resources, which constitute firms' AI readiness, influence the likelihood of AI adoption in manufacturing companies.

Based on organisational readiness for change (Weiner, 2009), we structure AI readiness according to the RBV (Barney, 1991; Grant, 1991; Bharadwaj, 2000) into two dimensions that represent the different resources required for AI adoption: technological AI readiness, which includes tangible assets, and organisational AI readiness, which includes both intangible and human resources. We further use this framework to empirically analyse the readiness of German manufacturing companies for AI adoption in production processes.

Through descriptive analysis, three notable findings emerge. First, regarding the readiness of manufacturing companies, the majority of manufacturers achieve a medium AI readiness level. Our results are similar to the analyses of AI readiness by Lerch et al. (2022), but in comparison they show a general increase in AI readiness in the manufacturing sector (with the exception of high readiness). This might be due to the fact that Lerch et al. (2022) use older data and that firms in the manufacturing sector are preparing for AI to a greater extent and taking appropriate measures. However, it should also be noted that the two AI readiness models draw on different factors, which makes a direct comparison more difficult. Second, our results show that AI readiness is strongly influenced by structural conditions in the manufacturing firms, which is consistent with the findings of recent studies (Chatterjee et al., 2021). Our results suggest that the company size significantly influences AI readiness (Mikalef et al., 2019a; Chatterjee et al., 2021), with small manufacturers prioritising organisational preparedness, whereas larger companies demonstrate greater technological readiness. This difference may stem from various resource constraints, such as financial limitations and a shortage of specialised personnel, coupled with uncertainties regarding the return on investment of technology (Jöhnk et al., 2021). Third, despite relatively high AI readiness levels, we show empirically that actual AI adoption in manufacturing remains limited. We measure an adoption rate of around 14 per cent for AI in the production context in Germany. This result on AI adoption is consistent with empirical data from recent studies. According to Rammer et al. (2022), AI use in the electronics industry in Germany is 11 per cent, with similar adoption rates visible in international comparisons, such as reported by McElheran et al. (2024), who measure AI adoption of 12 per cent among manufacturing companies in the United States.

The gap between AI readiness and AI adoption suggests some apprehension towards AI implementation, possibly caused by concerns such as uncertainty about how AI works and hesitancy, as highlighted in AI readiness framework studies (Alsheibani et al., 2018; Jöhnk et al., 2021; Heimberger et al., 2023). Additionally, AI's novelty in the traditional manufacturing industry aligns with Rogers' innovation diffusion curve (1983), indicating an early-stage adoption akin to innovators or early adopters. We summarise our finding derived from the outcomes of the empirical analysis.

- Finding 1: Despite a relatively high level of readiness for AI among manufacturing companies in Germany, actual adoption of AI in production is still low in practice. It seems that many companies are hesitant to use AI despite having strong AI-related resources that are relevant for the technical and organisational readiness to implement and work with AI.

To delve deeper into this phenomenon, we conducted multiple regression analyses. Our results unveil the varying significance of technological, organisational, and combined AI readiness in exploring the likelihood of AI adoption in manufacturing. Initially, while technological AI readiness is considered a fundamental prerequisite for firms to adopt AI solutions, our analysis does not reveal significant differences between various levels of technological AI readiness in explaining the odds of AI adoption. Nonetheless, the estimated odds ratios affirm the anticipated relationship, indicating a higher likelihood of AI adoption with increased technological AI readiness. In contrast, organisational AI readiness emerges as a pivotal factor, with companies exhibiting high organisational readiness being twice as likely to adopt AI compared to those with low organisational readiness. This result contradicts the study by Merhi and Harfouche (2024), which finds that the technological side is more vital for AI adoption than organisational factors. Despite this finding, Merhi and Harfouche (2024) also emphasise the importance of organisational factors, which is consistent with our finding about combined AI readiness. When considering Germany's manufacturing industry as a whole, our models consistently demonstrate that combined AI readiness significantly contributes to explaining AI adoption. This finding aligns with recent literature, underscoring AI's dual nature, which encompasses both technological complexity and organisational challenges, rather than thinking one-dimensionally (Mikalef et al., 2019a, 2019b, 2020; Mikalef and Gupta, 2021; Steininger et al., 2022; Merhi and Harfouche, 2024). These findings underscore the multifaceted nature of AI adoption in manufacturing, emphasizing the intertwined roles of resources relevant to technological and organisational preparedness. It is therefore important for firms to strengthen both technological and organisational resources in order to be better prepared for AI adoption and to avoid a siloed perspective. They provide valuable insights for policymakers and practitioners aiming to facilitate AI integration within manufacturing firms. In summary, we summarise the following finding.

- Finding 2: Manufacturing companies that consider both technological and organisational aspects and create holistic AI readiness are more likely to implement AI in a production context.

In our regression analysis, we researched into additional structural characteristics that play a significant role in the uptake of AI solutions in production (Rammer et al., 2022; McElheran et al., 2024). Notably, the features of manufactured products emerge as pivotal factors influencing the decision to integrate AI into production processes (McElheran et al., 2024). Specifically, for manufacturers dealing with highly complex products, the adoption of AI proves notably compelling, aligning with findings by Kinkel et al. (2022). This trend is especially pronounced in complex production processes often associated with high-tech products in smaller batch sizes (Hobday, 1998). This pattern is particularly reflected in the sector analysis, where the automotive industry, identified as a complex and cost-intensive sector (Demlehner et al., 2021), notably stands out in AI adoption for production processes. In contrast, our results indicate that batch size and the position of a firm in the value chain, do not significantly contribute to the explanatory power of our analysis. Therefore, we summarise.

- Finding 3: The adoption of AI in the manufacturing industry is significantly influenced by the structural characteristics of the companies operating in this sector. Certain factors exert pressure and promote the introduction of AI, while other factors impose distinctive constraints. In particular, companies that manufacture complex products, especially in highly specialised industries such as automotive, are more attuned to AI adoption.

Finally, our analysis underscores the critical importance of differentiating between high and medium levels of AI readiness. Conversely, distinguishing between lower levels of factors relevant for readiness seems not to yield meaningful insights regarding AI adoption. In this regard, our study additionally emphasises the significant role that firm size plays (Collins et al., 2021; Rammer et al., 2022; McElheran et al., 2024) and reveals a U-shaped relationship between firm size and AI adoption. Controlling for sector affiliation, batch size, product complexity, and AI readiness, larger firms demonstrate a significantly higher probability of using AI compared to medium-sized firms, while very small firms seems also to exhibit a higher probability. This correlation becomes particularly clear for manufacturers of complex products, the differences between companies with different levels of AI readiness are even more pronounced here.

- Finding 4: The relationship between firm size and AI adoption follow a U-shape. Larger and very small manufacturing companies demonstrate a higher probability of AI adoption compared to medium-sized companies.

Additional multivariate analysis with respect to the significance of the firm size show that the introduction of AI at smaller companies is influenced to a relevant extent by AI readiness. Conversely, for larger companies, the adoption of AI is primarily influenced by structural factors such as company size and the specific industry they operate in, AI readiness does not provide any additional explanation.

6. Conclusions

This study makes several important contributions to the research field by examining how AI readiness affects the likelihood of AI adoption in the production processes of manufacturing firms. The implications of this research are far-reaching, making contributions to production research and enhancing theoretical discussions across multiple domains.

6.1. Theoretical contributions

Building on the organisational readiness for change of companies, which we conceptualise based on the RBV, we propose a framework to analyse the role of various types of resources, and their combinations, in relation to technological and organisational readiness for the adoption of AI solutions in production companies. We distinguish between two interrelated dimensions of analysis: AI readiness and AI adoption: AI readiness serves as the foundation, representing a firm's technological and organisational readiness to adopt AI solutions (Alsheibani et al., 2019; Jöhnk et al., 2021; Horvat and Heimberger, 2022; Heimberger et al., 2023; Horvat et al., 2023). The availability of these fundamental resources, on which AI readiness is built, increases the likelihood of successful AI implementation in the production context (Chatterjee et al., 2021; Ghani et al., 2022; Kinkel et al., 2023). The dimension of AI adoption provides a theoretical lens to explore the gap between technological and organisational readiness for AI and its actual implementation. This perspective underscores the critical role of deployment strategies in bridging this gap, offering valuable insights into the interplay between readiness and real-world AI adoption in production companies.

Our study introduces a novel approach to operationalising AI readiness by categorizing it into two dimensions: technological AI readiness and organisational AI readiness (see Fig. 1). This dual perspective leads to a combined AI readiness score, structured as an ordinal indicator with five levels: no readiness, low readiness, lower medium readiness, higher medium readiness, and high readiness (see Fig. 2). This operationalisation provides a more granular understanding of AI readiness, but is still simple enough for practical usage, and its implications for AI capability development in manufacturing companies, offering an approach that can be used in future research.

Empirically, we contribute to the literature by analysing unique data about German manufacturing firms from the 2022 GMS dataset. To the best of our knowledge, our study provides the first broad-based empirical research of the relationship between AI readiness and actual AI adoption. Our results empirically confirm that a combined AI readiness, which fosters both technological and organisational readiness, has a positive influence on AI adoption in a production context (Jöhnk et al., 2021; Uren and Edwards, 2023). Manufacturing firms adopt different strategies when building their AI readiness and developing and coordinating the associated resources for AI implementation, a result that is consistent with current research (Steininger et al., 2022; Horvat et al., 2023). In particular, we identify the significant role of structural characteristics, such as firm size, in these strategies: smaller manufacturers tend to prioritise organisational preparedness, focusing on change management and workforce readiness, while larger companies exhibit higher levels of technological readiness, leveraging more advanced digital infrastructures. These results contribute to the existing literature (Kinkel et al., 2022; Steininger et al., 2022; Horvat et al., 2023; McElheran et al., 2024) by highlighting the diverse AI readiness development strategies firms employ based on their characteristics.

Furthermore, we explore the role of structural and organisational characteristics in AI adoption (Chatterjee et al., 2021; Dwivedi et al., 2021; Steininger et al., 2022). Our findings show that structural factors such as company size and product complexity significantly influence the relationship between AI readiness and adoption. For example, our study identifies a U-shaped relationship between company size and AI adoption rates, with both small and large companies showing higher adoption levels than medium-sized firms. Additionally, we find that product complexity amplifies the relevance of various levels of combined AI readiness for AI adoption. These structural factors suggest that even when resources are available, certain structural characteristics and organisational configurations may hinder the adoption process, offering new insights into the barriers manufacturers face when implementing AI technologies.

6.2. Practical implications

The adoption of AI in production is a multidimensional challenge, requiring more than the availability of appropriate technology. Practitioners must promote readiness, which is important at both the organisational and technological levels, remain sensitive to industry- and company-specific dynamics, and implement targeted measures to promote AI readiness as companies move towards AI adoption. From a practical standpoint, our research offers valuable guidance for managers in manufacturing firms tasked with integrating AI solutions into their production operations.

First, our results reveal a persistent gap between AI readiness and actual AI adoption. Despite a large share of manufacturing firms exhibiting medium to high levels of AI readiness, adoption rates in production remain low. This indicates that while resource availability is important, it alone does not ensure implementation. Managers should use our readiness assessment tool to evaluate their condition (see Hussain and Papastathopoulos (2022)) and complement this by implementing targeted internal initiatives (Uren and Edwards, 2023). Early steps such as awareness-building, employee engagement, and pilot projects can help reduce hesitancy and clarify the practical value of AI in production. This implication also extends to policymakers, who should foster investment in AI technologies and create incentives to accelerate AI uptake in manufacturing (Rammer et al., 2022; Kinkel et al., 2023).

Second, our analysis shows that combined AI readiness, i.e. the integration of both technological and organisational resources, significantly increases the likelihood of AI adoption. While technological readiness remains a necessary foundation, organisational readiness exerts a greater influence on adoption. Managers should therefore prioritise the development of organisational capabilities, including intangible and human resources, before making substantial investments in technical infrastructure. An isolated focus on technology is insufficient (Jöhnk et al., 2021; Uren and Edwards, 2023). Using our combined AI readiness framework, firms can take targeted steps to enhance both dimensions and improve their chances of successful AI adoption.

Third, we find that firms producing complex, high-tech products, especially in specialised sectors such as the automotive industry, are more likely to adopt AI (Kinkel et al., 2022). These firms face both greater pressure and more compelling opportunities for AI implementation (Demlehner et al., 2021). For this reason, adoption strategies must be aligned with structural characteristics. Managers should tailor their AI adoption strategies to reflect industry-specific and product-related factors. In particular, manufacturers of complex or customised products should prioritise AI use cases that enhance process efficiency, product quality, or innovation.

Fourth, our findings indicate that AI adoption follows a U-shaped pattern in relation to firm size. Small and large firms have distinct advantages or motivations for adopting AI, whereas medium-sized firms may face unique challenges (Sjödin et al., 2021; Kinkel et al., 2022; Zavodna et al., 2024). Smaller firms are highly dependent on their level of AI readiness, whereas adoption in larger firms is more strongly influenced by structural characteristics. Medium-sized firms may struggle with both limited agility and constrained resources, which can slow adoption (Kinkel et al., 2022). Based on this, we recommend that firms adapt their AI strategies to their specific size: Small firms should focus on strengthening their AI readiness and consider seeking external support. Medium-sized firms may benefit from additional resources, partnerships, or collaboration to overcome capacity limitations. Large firms should address internal structural barriers and ensure that AI initiatives are aligned with broader organisational objectives.

6.3. Limitations and future research

While our study provides valuable insights into AI adoption in the manufacturing industry, certain limitations pave the way for future research opportunities.

Firstly, while the AI readiness indices we developed (technological, organisational and combined AI readiness) capture key factors influencing adoption, the scope of our model remains focused on a selected set of relevant factors. We acknowledge that additional factors, both technical and organisational, may also play a crucial role in shaping AI readiness and adoption outcomes. In particular, our current model does not explicitly incorporate ethical and societal aspects, which are gaining increasing importance in both academic discourse and practical implementation of AI (Heimberger et al., 2024). For instance, concerns about job replacement, as highlighted by Frey and Osborne (2017), can significantly influence employee attitudes and, consequently, organisational readiness. Similarly, data privacy concerns, especially in data-intensive production environments, can create barriers to AI adoption, both from a regulatory and workforce trust perspective (Wieringa et al., 2021). Although these factors were not within the primary scope of our study, we see them as important contextual factors that deserve deeper investigation. Future research could meaningfully expand on our readiness framework by integrating ethical and societal considerations alongside additional organisational and technological variables. This broader approach could provide a more nuanced understanding of AI readiness and adoption and support the development of holistic and context-sensitive implementation strategies.

Secondly, in our analysis we assume an additive relationship between the dimensions and do not analyse how technological and organisational AI readiness and their individual factors might influence each other. We see potential here for future research that analyses how different factors of technological and organisational readiness are linked and how they can mutually promote or hinder each other. Structural equation modelling approaches, which can also be used to analyse the relationships between the independent variables, are worth considering in future research on AI readiness factors, as they have already been applied to AI adoption (Baabdullah, 2024). Another possibility would be to further examine the factors in terms of their weighting and thus identify particularly crucial factors, as proposed by Merhi and Harfouche (2024).

Third, we highlight that while firms may possess the necessary resources, the ability to effectively coordinate and deploy these resources is equally critical. This perspective aligns with the traditional capability-based view within the RBV framework (Amit and Schoemaker, 1993; Teece et al., 1997), which posits that firms require company-specific, unique (dynamic) capabilities to align their resource base with actionable strategies, thereby achieving competitive advantages (Mikalef et al., 2019a; Mikalef and Gupta, 2021; Steininger et al., 2022; Peretz-Andersson et al., 2024). Future research should delve deeper into identifying the specific capabilities that play a pivotal role and exploring how firms develop these capabilities.

Fourth, for the control of a firm's market context and further internal dynamics, we only include a selection of variables in our data analysis. It would be beneficial for future studies to incorporate additional factors, such as competitive strategy, management support, risk propensity or financial resources, to provide a more comprehensive understanding of the factors influencing AI adoption in manufacturing. It would be important to specifically examine the different conditions for larger, medium and small companies in the analyses.

From a conceptual point of view, our study focuses on the fundamental analysis of the adoption of AI. We analyse those companies that actually use AI in their production process not going into detail of the extend of use or the contribution to the production. By doing that, our study covers four major AI applications within the production context. Future research could extend this view to include a broader range of production applications and explore the adoption of AI in additional areas of the production process such as shift allocation, or task assignment as well as in other areas of manufacturing companies, such as product development, procurement, or marketing. Since we consider AI adoption as a binary variable (Dahlke et al., 2024; Zhan et al., 2024), our analyses do not allow any conclusions to be drawn about the status and intensity of use (as proposed by Kinkel et al. (2022, 2023) or McElheran et al. (2024)). In future empirical studies, this would certainly be an interesting addition in order to better understand the state of adoption at the process level and to be able to make better statements about the depth of AI use in German manufacturing firms.

While our study focuses on analysing AI adopters in the German manufacturing industry, future research could shed light on non-AI adopters by exploring various cases such as failed adoption, discontinued adoption, unexpected outcomes, and the general relationship between AI adoption and expected firm performance. Despite a general willingness and increasing readiness to adopt AI, our results show that adoption remains limited. We do not address cases where companies, although AI-ready, ultimately decided against adoption, or where AI adoption efforts failed or did not deliver the expected outcomes (Sun, 2013). Future studies could investigate these aspects to uncover barriers to adoption and better understand why some AI initiatives are unsuccessful or abandoned. Longitudinal case study research would be particularly suitable for in-depth analysis of individual implementation processes (Langley and Truax, 1994). Additionally, examining the relationship between AI adoption and firm performance (Plewa et al., 2012) could help explore the economic rationale behind AI investments, identify conditions under which AI leads to performance improvements (see Baabdullah (2024)), and explain why some firms may choose not to implement AI despite having the readiness in place. Such research would provide a more nuanced understanding of the practical limitations of AI adoption and its broader impact on business strategy and competitive advantage.

Finally, our study focuses solely on the industry in Germany, limiting the generalisability of our findings to other countries and regions. Future studies could expand their scope to include multiple countries, allowing for comparisons to assess the influence of country-specific circumstances on AI adoption readiness. In addition, it would be of great interest to repeat the analyses in the near future, as the rapid development of the applications offered, the increasing usability of ready-made solutions and the development of the support structure for AI implementation will significantly change AI adoption. Thus, future AI adoption analyses based on GMS may be able to show further movement of companies in Germany along Rogers (1983) diffusion curve in terms of AI adoption.

CRediT authorship contribution statement

Heidi Heimberger: Formal analysis, Writing – original draft, Investigation, Writing – review & editing, Conceptualization. **Djerdj Horvat:** Writing – original draft, Conceptualization, Supervision, Writing – review & editing, Formal analysis. **Angela Jäger:** Supervision, Data curation, Methodology, Conceptualization, Writing – original draft, Formal analysis. **Frank Schultmann:** Supervision.

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Appendix. 7

Table 3
Sample characteristics of analysed data, N = 1130

		%
Firm size	<50 employees	44 %
	50 to 249 employees	42 %
	>250 employees	14 %
Sector	Metal industry	22 %
	Mechanical engineering	20 %
	Rubber and plastics industry	15 %
	Food and beverage industry	9 %
	Electrical/electronics industry	8 %
	Chemical and pharmaceutical	5 %
	Vehicle construction	5 %
	Others	15 %
Product complexity	Simple complexity of products	21 %
	Medium complexity of products	49 %
	High complexity of products	30 %
Batch size	Single lot manufacturing	26 %
	Small/medium lot manufacturing	57 %
	Big lot manufacturing	18 %
N = 1130		

Table 4
Distribution of the constitutive factors for technological and organisational AI readiness in German manufacturing

Technological AI readiness		
Data availability	No data availability (none of the systems used)	18 %
	Basic data availability (1 or 2 systems used)	64 %
	Large data availability (3 or 4 systems used)	18 %
IT infrastructure	No employees assigned to IT infrastructure	31 %
	<5 % IT employees	43 %
	5 % or more IT employees	26 %
Data security	No security measures implemented	7 %
	A few security measures (1 or 2 of 4 levels)	60 %
	Various security (3 or 4 of 4 levels)	33 %
Organisational AI readiness		
Skills	No digital skills required (no digital tools used)	47 %
	Few digital skills required (at least 1 digital tool)	35 %
	Digital skills required (more than 1 tool)	18 %
Training	No training measures offered	18 %
	Few training measures offered (1 of 3)	31 %
	Several training measures offered (at least 2)	51 %
Innovation culture	No innovation culture	26 %
	Basic innovation culture (1 of 3)	29 %
	Open innovation culture (at least 2)	44 %
Cooperation	No cooperation	43 %
	Basic R&D cooperation (1 of 3)	20 %
	Broad R&D cooperation (at least 2)	37 %

Table 5
AI readiness and AI adoption by manufacturers in Germany depending on structural and production features of the firms

	Combined AI readiness					AI adoption
	no	low	low medium	high medium	high	
*Firm size (# of employees) ***/****						
up to 49 employees	6 %	31 %	**34 %**	22 %	6 %	12 %
50 to 99 employees	3 %	21 %	29 %	**32 %**	15 %	14 %
100 to 499 employees	1 %	9 %	25 %	**39 %**	27 %	14 %
500 or more employees	0 %	2 %	9 %	36 %	**53 %**	**28 %**
*Sector groups (NACE rev. 2) ***/****						
metal products	3 %	27 %	27 %	**29 %**	14 %	14 %
machinery	**7 %**	**32 %**	30 %	21 %	10 %	11 %
rubber and plastics industry	2 %	5 %	**39 %**	33 %	21 %	18 %
food and beverage industry	5 %	21 %	29 %	**32 %**	14 %	14 %
chemical and pharmaceutical industry	1 %	5 %	31 %	**41 %**	21 %	7 %
electrical/electronic industry	1 %	15 %	**32 %**	31 %	22 %	12 %
automotive industry	2 %	17 %	17 %	31 %	**33 %**	**31 %**
other sectors	**7 %**	**28 %**	25 %	26 %	14 %	12 %
*Batch size ***/***						
single lot manufacturing	3 %	27 %	**31 %**	27 %	12 %	11 %
small/medium lot manufacturing	4 %	20 %	30 %	**31 %**	16 %	13 %
big lot manufacturing	2 %	15 %	23 %	**31 %**	29 %	**20 %**
*Product complexity ***/****						
simple products	7 %	30 %	**34 %**	22 %	8 %	8 %
medium complex products	3 %	22 %	30 %	**31 %**	15 %	13 %
complex products	2 %	13 %	24 %	**34 %**	27 %	**20 %**
Position in the value chain (multiple entries possible)						
producer of finished goods for consumers ***/n.s.	5 %	26 %	**29 %**	26 %	14 %	12 %
final products for industry n.s./*	3 %	18 %	28 %	**33 %**	18 %	12 %
supplier (system -, part -) ***/**	2 %	18 %	28 %	**32 %**	21 %	**17 %**
contract manufacturer **/n.s.	4 %	27 %	**30 %**	28 %	11 %	10 %
Total	3 %	21 %	**29 %**	**30 %**	17 %	14 %

Note: Group comparison using Kruskall-Wallis test. Significance levels: ***p < 0.01; **p < 0.05; *p < 0.1. Modal values are marked in bold.

Table 6
Summary of estimated results of the logistic regression model estimations on AI adoption in production for smaller firms (less than 100 employees)

Construct	Model H1 Technological AI readiness	Model H2 Organisational AI readiness	Model H3 Combined AI readiness
	Sig	Sig	Sig
Firm and production characteristics			
Firm size	n.s.	n.s.	n.s.
Sector	n.s.	n.s.	n.s.

(*continued on next page*)

Table 6 (*continued*)

Construct	Model H1 Technological AI readiness	Model H2 Organisational AI readiness	Model H3 Combined AI readiness
	Sig	Sig	Sig
Product complexity	**	**	**
Batch size	n.s.	n.s.	n.s.
Value chain position	n.s.	n.s.	n.s.
AI readiness			
Technological AI readiness	*		
Organisational AI readiness		**	
Combined AI readiness			**
Model fit			
Log Likelihood/sig.	531,659**	531,07***	527,60**
Cox & Snell R2	3,5 %	3,6 %	4,0 %
Nagelkerke R2	6,6 %	6,8 %	7,6 %
Explanatory contribution of the AI construct (delta Log Likelihood)	5839*	6,43**	9,90**

N = 734; firms with less than 100 employees.
Significance levels: ***p < 0.01; **p < 0.05; *p < 0.1.

Table 7
Summary of estimated results of the logistic regression model estimations on AI adoption in production for small firms (less than 50 employees)

Construct	Model H1 Technological AI readiness	Model H2 Organisational AI readiness	Model H3 Combined AI readiness
	Sig	Sig	Sig
Firm and production characteristics			
Firm size	n.s.	n.s.	n.s.
Sector	n.s.	n.s.	*
Product complexity	**	***	***
Batch size	n.s.	n.s.	n.s.
Value chain position	n.s.	n.s.	n.s.
AI readiness			
Technological AI readiness	**		
Organisational AI readiness		**	
Combined AI readiness			***
Model fit			
Log Likelihood/sig.	337,726**	338,57***	334,71***
Cox & Snell R2	5,7 %	5,6 %	6,3 %
Nagelkerke R2	11,1 %	10,8 %	12,2 %
Explanatory contribution of the AI construct (delta Log Likelihood)	8594**	7,75**	11,61***

N = 502; firms with less than 50 employees.
Significance levels: ***p < 0.01; **p < 0.05; *p < 0.1.

Table 8
Summary of estimated results of the logistic regression model estimations on AI adoption in production for larger firms (100 or more employees)

Construct	Model H1 Technological AI readiness	Model H2 Organisational AI readiness	Model H3 Combined AI readiness
	Sig	Sig	Sig
Firm and production characteristics			
Firm size	**	**	**
Sector	*	*	*
Product complexity	**	***	***
Batch size	n.s.	n.s.	n.s.
Value chain position	n.s.	n.s.	n.s.
AI readiness			
Technological AI readiness	n.s.		
Organisational AI readiness		n.s.	
Combined AI readiness			n.s.
Model fit			
Log Likelihood/sig.	299,790***	300,82***	298,56***
Cox & Snell R2	12,0 %	11,8 %	12,3 %
Nagelkerke R2	20,4 %	20,0 %	20,9 %
Explanatory contribution of the AI construct (delta Log Likelihood)	2663	1,63	3,90

N = 396; firms with 100 and more employees.
Significance levels: ***p < 0.01; **p < 0.05; *p < 0.1.

Data availability

The data that has been used is confidential.

References

Aboelmaged, M.G., 2014. Predicting e-readiness at firm-level: an analysis of technological, organizational and environmental (TOE) effects on e-maintenance readiness in manufacturing firms. Int. J. Inf. Manag. 34, 639–651.
Ajzen, I., 1991. The theory of planned behavior. Organ. Behav. Hum. Decis. Process. 50, 179–211.
Akinsolu, M.O., 2022. Applied artificial intelligence in manufacturing and industrial production systems: PEST considerations for engineering managers. IEEE Eng. Manag. Rev. 51, 52–62.
Al-Hujran, O., Al-Lozi, E.M., Al-Debei, M.M., Maqableh, M., 2018. Challenges of cloud computing adoption from the TOE framework perspective. Int. J. E Bus. Res. 14, 77–94.
Alsheibani, S., Cheung, Y., Messom, C., 2018. Artificial intelligence adoption: AI-Readiness at Firm-Level: Research-in-Progress. Twenty-Second Pacific Asia Conference on Information Systems.
Alsheibani, S., Cheung, Y., Messom, C., 2019. Factors inhibiting the adoption of artificial intelligence at organizational-level: a preliminary investigation. Twenty-fifthAmericas Conference on Information Systems.
Amit, R., Schoemaker, P.J.H., 1993. Strategic assets and organizational rent. Strateg. Manag. J. 14, 33–46.
Antony, J., Sony, M., McDermott, O., Jayaraman, R., Flynn, D., 2023. An exploration of organizational readiness factors for Quality 4.0: an intercontinental study and future research directions. Int. J. Qual. Reliab. Manag. 40, 582–606.
Armbruster, H., Bikfalvi, A., Kinkel, S., Lay, G., 2008. Organizational innovation: the challenge of measuring non-technical innovation in large-scale surveys. Technovation 28, 644–657.
Audretsch, D.B., Lehmann, E.E., Schenkenhofer, J., 2018. Internationalization strategies of hidden champions: lessons from Germany. Multinatl. Bus. Rev. 26, 2–24.
Awamleh, F.T., Bustami, A.N., 2022. Examine the mediating role of the information technology capabilities on the relationship between artificial intelligence and competitive advantage during the COVID-19 pandemic. Sage Open 12.
Azambuja, A.J.G. de, Plesker, C., Schützer, K., Anderl, R., Schleich, B., Almeida, V.R., 2023. Artificial intelligence-based cyber security in the Context of Industry 4.0—A Survey. Electronics 12, 1–18.
Baabdullah, A.M., 2024. The precursors of AI adoption in business: towards an efficient decision-making and functional performance. International Journ 75, 1–26.
Barney, J., 1991. Firm resources and sustained competitive advantage. J. Manag. 17, 99–120.
Benner, M.J., Waldfogel, J., 2020. Changing the channel: digitization and the rise of "middle tail" strategies. Strateg. Manag. J. 86, 1–24.
Bettoni, A., Matteri, D., Montini, E., Gładysz, B., Carpanzano, E., 2021. An AI adoption model for SMEs: a conceptual framework. IFAC-PapersOnLine 54, 702–708.
Bharadwaj, A.S., 2000. A resource-based perspective on information technology capability and firm performance: an empirical investigation. MIS Q. 169–196.
Bikfalvi, A., Jäger, A., Lay, G., 2014. The incidence and diffusion of teamwork in manufacturing – evidences from a Pan-European survey. J. Organ. Change Manag. 27, 206–231.
Bikfalvi, A., Lay, G., Maloca, S., Waser, B.R., 2013. Servitization and networking: large-scale survey findings on product-related services. Service Business 7, 61–82.
Boavida, N., Candeias, M., 2021. Recent automation trends in Portugal: implications on industrial productivity and employment in automotive sector. Societies 11, 1–17.
Bokrantz, J., Subramaniyan, M., Skoogh, A., 2023. Realising the promises of artificial intelligence in manufacturing by enhancing CRISP-DM. Prod. Plann. Control 1–21.
Bonnard, R., Da Arantes, M.S., Lorbieski, R., Vieira, K.M.M., Nunes, M.C., 2021. Big data/analytics platform for industry 4.0 implementation in advanced manufacturing context. Int. J. Adv. Des. Manuf. Technol. 117, 1959–1973.
Broedner, P., Kinkel, S., Lay, G., 2009. Productivity effects of outsourcing. Int. J. Oper. Prod. Manag. 29, 127–150.
Chatterjee, S., Rana, N.P., Dwivedi, Y.K., Baabdullah, A.M., 2021. Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model. Technol. Forecast. Soc. Change 170, 1–14.
Chiang, L.H., Braun, B., Wang, Z., Castillo, I., 2022. Towards artificial intelligence at scale in the chemical industry. AIChE J. 68, 1–20.
Collins, C., Dennehy, D., Conboy, K., Mikalef, P., 2021. Artificial intelligence in information systems research: a systematic literature review and research agenda. Int. J. Inf. Manag. 60, 1–17.
Dachs, B., Biege, S., Borowiecki, M., Lay, G., Jäger, A., Schartinger, D., 2014. Servitisation of European manufacturing: evidence from a large scale database. Serv. Ind. J. 34, 5–23.
Dachs, B., Zahradnik, G., 2022. From few to many: main trends in the internationalization of business R&D. Transnational Corporation 29, 107–134.
Dahlke, J., Beck, M., Kinne, J., Lenz, D., Dehghan, R., Wörter, M., Ebersberger, B., 2024. Epidemic effects in the diffusion of emerging digital technologies: evidence from artificial intelligence adoption. Res. Pol. 53, 1–15.
Damanpour, F., Schneider, M., 2006. Phases of the adoption of innovation in organizations: effects of environment, Organization and top Managers1. Br. J. Manag. 17, 215–236.
Davis, F.D., 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Q. 13, 319–340.
Demlehner, Q., Schoemer, D., Laumer, S., 2021. How can artificial intelligence enhance car manufacturing? A Delphi study-based identification and assessment of general use cases. Int. J. Inf. Manag. 58, 1–14.
DeStefano, T.J., Teodorovicz, T., Cho, J., Kim, H., Paik, J., 2022. What Determines AI Adoption? Academy of Management Proceedings 2022.
Dohale, V., Akarte, M., Gunasekaran, A., Verma, P., 2022. Exploring the role of artificial intelligence in building production resilience: learnings from the COVID-19 pandemic. Int. J. Prod. Res. 1–17.
Drobot, A.T., 2020. Industrial transformation and the digital revolution: a focus on artificial intelligence, data science and data engineering. In: 2020 ITU Kaleidoscope: Industry-Driven Digital Transformation (ITU K), Ha Noi, Vietnam. 12/7/2020 - 12/11/2020. IEEE, pp. 1–11.
Dubey, R., Gunasekaran, A., Childe, S.J., Bryde, D.J., Giannakis, M., Foropon, C., Roubaud, D., Hazen, B.T., 2020. Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: a study of manufacturing organisations. Int. J. Prod. Econ. 226, 1–12.
Dwivedi, Y.K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., 2021. Artificial Intelligence (AI): multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. Int. J. Inf. Manag. 57, 1–47.
Escobar, C., Arinez, J., Morales-Menendez, R., 2020. Process-Monitoring-for-Quality - a step forward in the zero defects vision. In: SAE Technical Paper Series. WCX SAE World Congress Experience. APR. 21, 2020. SAE International400 Commonwealth Drive, Warrendale, PA, United States.
European Commission, 2024. European innovation scoreboard. https://research-and-innovation.ec.europa.eu/statistics/performance-indicators/european-innovation-scoreboard_en.
Fahle, S., Prinz, C., Kuhlenkötter, B., 2020. Systematic review on machine learning (ML) methods for manufacturing processes – identifying artificial intelligence (AI) methods for field application. Proced. CIRP 93, 413–418.
Fishbein, M., Ajzen, I., 1975. Belief, Attitude, Intention and Behavior: an Introduction to Theory and Research. Addison-Wesley, Reading, Mass.
Fraunhofer Institute for Systems and Innovation Research ISI, 2024. Erhebung Modernisierung der Produktion. https://www.isi.fraunhofer.de/de/themen/industrielle-wettbewerbsfaehigkeit/erhebung-modernisierung-produktion.html. (Accessed 20 December 2024).
Frey, C.B., Osborne, M.A., 2017. The future of employment: how susceptible are jobs to computerisation? Technol. Forecast. Soc. Change 114, 254–280.
Garrison, G., Wakefield, R.L., Kim, S., 2015. The effects of IT capabilities and delivery model on cloud computing success and firm performance for cloud supported processes and operations. Int. J. Inf. Manag. 35, 377–393.
Ghani, E.K., Ariffin, N., Sukmadilaga, C., 2022. Factors influencing artificial intelligence adoption in publicly listed manufacturing companies: a technology, Organisation, and environment approach. International Journal of Applied Economics, Finance and Accounting 14, 108–117.
Ghobakhloo, M., Ching, N.T., 2019. Adoption of digital technologies of smart manufacturing in SMEs. Journal of Industrial Information Integration 16, 1–14.
Grant, R.M., 1991. The Resource-based theory of competitive advantage: implications for strategy formulation. California Management Review. University of California, Berkeley, CA, pp. 114–135.
Gupta, M., George, J.F., 2016. Toward the development of a big data analytics capability. Inf. Manag. 53, 1049–1064.
Hameed, M.A., Counsell, S., Swift, S., 2012. A conceptual model for the process of IT innovation adoption in organizations. J. Eng. Technol. Manag. 29, 358–390.
Hartley, J.L., Sawaya, W.J., 2019. Tortoise, not the hare: digital transformation of supply chain business processes. Bus. Horiz. 62, 707–715.
Heimberger, H., Horvat, D., Schultmann, F., 2023. Assessing AI-Readiness in Production—A conceptual approach. In: Huang, C.-Y., Dekkers, R., Chiu, S.F., Popescu, D., Quezada, L. (Eds.), Intelligent and Transformative Production in Pandemic Times. Springer International Publishing, Cham, pp. 249–257.
Heimberger, H., Horvat, D., Schultmann, F., 2024. Exploring the factors driving AI adoption in production: a systematic literature review and future research agenda. Inf. Technol. Manag. 1–17.
Hobday, M., 1998. Product complexity, innovation and industrial organisation. Res. Pol. 26, 689–710.
Holmström, J., 2022. From AI to digital transformation: the AI readiness framework. Bus. Horiz. 65, 329–339.
Horvat, D., Baumgartner, M., Kinkel, S., Mikalef, P., 2023. Examining heterogeneous patterns of AI capabilities. In: Alfnes, E., Romsdal, A., Strandhagen, J.O., Cieminski, G. von, Romero, D. (Eds.), Advances in Production Management Systems. Production Management Systems for Responsible Manufacturing, Service, and Logistics Futures, 690. Springer, Nature Switzerland, Cham, pp. 619–633.
Horvat, D., Heimberger, H., 2022. AI readiness: an integrated socio-technical framework. International Conference of Production Research Americas 2022. https://doi.org/10.1007/978-3-031-36121-0_69.
Hussain, M., Papastathopoulos, A., 2022. Organizational readiness for digital financial innovation and financial resilience. Int. J. Prod. Econ. 243, 1–15.
Issa, H., Jabbouri, R., Palmer, M., 2022. An artificial intelligence (AI)-readiness and adoption framework for AgriTech firms. Technol. Forecast. Soc. Change 182, 1–17.
Jäger, A., Maloca, S., 2022. Dokumentation Der Umfrage Modernisierung Der Produktion 2022. Fraunhofer ISI.
Javaid, M., Haleem, A., Singh, R.P., Suman, R., 2021. Significant applications of big data in industry 4.0. Journal of Industrial Integration and Management 6, 429–447.

Jöhnk, J., Weißert, M., Wyrtki, K., 2021. Ready or not, AI Comes— an interview Study of organizational AI readiness factors. Business & Information Systems Engineering 63, 5–20.
Jones, R.A., Jimmieson, N.L., Griffiths, A., 2005. The impact of organizational culture and reshaping capabilities on change implementation success: the mediating role of readiness for change. J. Manag. Stud. 42, 361–386.
Kagermann, H., 2015. Change through Digitization—Value Creation in the Age of Industry 4.0. In: Albach, H., Meffert, H., Pinkwart, A., Reichwald, R. (Eds.), Management of Permanent Change. Springer, Fachmedien Wiesbaden, Wiesbaden, pp. 23–45.
Kapoor, K., Bigdeli, A.Z., Dwivedi, Y.K., Raman, R., 2021. How is COVID-19 altering the manufacturing landscape? A literature review of imminent challenges and management interventions. Ann. Oper. Res. 1–33.
Kelly, P., Hegarty, J., Barry, J., Dyer, K.R., Horgan, A., 2017. A systematic review of the relationship between staff perceptions of organizational readiness to change and the process of innovation adoption in substance misuse treatment programs. J. Subst. Abuse Treat. 80, 6–25.
Kinkel, S., Baumgartner, M., Cherubini, E., 2022. Prerequisites for the adoption of AI technologies in manufacturing – evidence from a worldwide sample of manufacturing companies. Technovation 110, 1–17.
Kinkel, S., Capestro, M., Di Maria, E., Bettiol, M., 2023. Artificial intelligence and relocation of production activities: an empirical cross-national study. Int. J. Prod. Econ. 261, 1–14.
Kinkel, S., Kirner, E., Armbruster, H., Jager, A., 2011. Relevance and innovation of production-related services in manufacturing industry. Int. J. Technol. Manag. 55, 263–273.
Kinkel, S., Lay, G., Maloca, S., 2007. Development, motives and employment effects of manufacturing offshoring of German SMEs. Int. J. Enterpren. Small Bus. 4, 256–276.
Kirner, E., Som, O., Jäger, A., 2015. Innovation strategies and patterns of Non-R&D-Performing and Non-R&D-Intensive firms. In: SOM, O., Kirner, E. (Eds.), Low-Tech Innovation. Springer International Publishing, Cham, pp. 91–111.
Klein, K.J., Sorra, J.S., 1996. The challenge of innovation implementation. Acad. Manag. Rev. 21, 1055–1080.
Kromrey, H., Roose, J., Strübing, J., 2016. Empirische Sozialforschung. utb GmbH, Stuttgart, Deutschland.
Kruskal, W.H., Wallis, W.A., 1952. Use of ranks in one-criterion variance analysis. J. Am. Stat. Assoc. 47, 583–621.
Kyvik Nordås, H., Klügl, F., 2021. Drivers of automation and consequences for jobs in engineering services: an agent-based modelling approach. Frontiers in robotics and AI 8, 1–16.
Langley, A., Truax, J., 1994. A process study OF new technology adoption IN smaller MANUFACTURING firms. J. Manag. Stud. 31, 619–652.
Lay, G., Copani, G., Jäger, A., Biege, S., 2010. The relevance of service in European manufacturing industries. J. Serv. Manag. 21, 715–726.
Lay, G., Maloca, S., 2004. Dokumentation der Umfrage Innovationen in der Produktion 2003. https://doi.org/10.24406/publica-fhg-292319.
Lee, J., Davari, H., Singh, J., Pandhare, V., 2018. Industrial Artificial Intelligence for industry 4.0-based manufacturing systems. Manufacturing Letters 18, 20–23.
Lerch, C.M., Heimberger, H., Jäger, A., Horvat, D., Bitter, J., 2021. KI-Readiness im Verarbeitenden Gewerbe: stand und Perspektiven für Baden-Württemberg. https://www.i40-bw.de/wp-content/uploads/2021/12/KI-Readiness-im-Verarbeitenden-Gewerbe.pdf. (Accessed 20 July 2023).
Lerch, C.M., Heimberger, H., Jäger, A., Horvat, D., Schultmann, F., 2022. AI-readiness and production resilience: empirical evidence from German manufacturing in times of the Covid-19 pandemic. Int. J. Prod. Res. 1–22.
Li, B., Hou, B., Yu, W., Lu, X., Yang, C., 2017. Applications of artificial intelligence in intelligent manufacturing: a review. Frontiers of Information Technology & Electronic Engineering 18, 86–96.
Lin, H.-F., Lin, S.-M., 2008. Determinants of e-business diffusion: a test of the technology diffusion perspective. Technovation 28, 135–145.
Lokuge, S., Sedera, D., Grover, V., Dongming, X., 2019. Organizational readiness for digital innovation: development and empirical calibration of a construct. Inf. Manag. 56, 445–461.
Mann, H.B., Whitney, D.R., 1947. On a Test of whether one of two random variables is stochastically larger than the other. Ann. Math. Stat. 18, 50–60.
Mantravadi, S., Li, C., Møller, C., 2019. Multi-agent Manufacturing Execution System (MES): Concept, Architecture & ML Algorithm for a smart factory case. In: Proceedings of the 21st International Conference on Enterprise Information Systems. 21st International Conference on Enterprise Information Systems, Heraklion, Crete, Greece. SCITEPRESS - Science and Technology Publications, pp. 477–482, 03.05.2019 - 05.05.2019.
McCauley, L., 2007. AI Armageddon and the three laws of robotics. Ethics Inf. Technol. 9, 153–164.
McElheran, K., Li, J.F., Brynjolfsson, E., Kroff, Z., Dinlersoz, E., Foster, L., Zolas, N., 2024. AI adoption in America: who, what, and where. J. Econ. Manag. Strat. 33, 375–415.
McGrath, R.G., MacMillan, I.C., Venkataraman, S., 1995. Defining and developing competence: a strategic process paradigm. Strateg. Manag. J. 16, 251–275.
Merhi, M.I., Harfouche, A., 2024. Enablers of artificial intelligence adoption and implementation in production systems. Int. J. Prod. Res. 62, 5457–5471.
Mikalef, P., Boura, M., Lekakos, G., Krogstie, J., 2019a. Big data analytics and firm performance: findings from a mixed-method approach. J. Bus. Res. 98, 261–276.
Mikalef, P., Fjortoft, S.O., Torvatn, H.Y., 2019b. Developing an artificial intelligence capability. A Theoretical Framework for Business Value, pp. 1–8.
Mikalef, P., Gupta, M., 2021. Artificial intelligence capability: conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. Inf. Manag. 58, 1–20.
Mikalef, P., Krogstie, J., Pappas, I.O., Pavlou, P., 2020. Exploring the relationship between big data analytics capability and competitive performance: the mediating roles of dynamic and operational capabilities. Inf. Manag. 57, 1–15.
Mubarok, K., Arriaga, E.F., 2020. Building a smart and intelligent factory of the future with industry 4.0 technologies. J. Phys. Conf. 1569, 1–7.
Oliveira, B.G., Liboni, L.B., Cezarino, L.O., Stefanelli, N.O., Miura, I.K., 2020. Industry 4.0 in systems thinking: from a narrow to a broad spectrum. Syst. Res. Behav. Sci. 37, 593–606.
Oliveira, T., Marins, M.F., 2011. Literature review of information technology adoption models at firm level. Electron. J. Inf. Syst. Eval. 14, 110–121.
Oliveira, T., Thomas, M., Espadanal, M., 2014. Assessing the determinants of cloud computing adoption: an analysis of the manufacturing and services sectors. Inf. Manag. 51, 497–510.
Olsowski, S., Schlögl, S., Richter, E., Bernsteiner, R., 2022. Investigating the potential of AutoML as an instrument for fostering AI adoption in SMEs. In: Uden, L., Ting, I.-H., Feldmann, B. (Eds.), Knowledge Management in Organisations. 16th International Conference, KMO 2022, Hagen, Germany, July 11–14, 2022, Proceedings, first ed. Springer International Publishing; Imprint Springer, Cham, pp. 360–371. 1593.
Peretz-Andersson, E., Tabares, S., Mikalef, P., Parida, V., 2024. Artificial intelligence implementation in manufacturing SMEs: a resource orchestration approach. Int. J. Inf. Manag. 77, 1–23.
Pichlak, M., 2016. The innovation adoption process: a multidimensional approach. J. Manag. Organ. 22, 476–494.
Pierce, J.L., Delbecq, A.L., 1977. Organization structure, individual attitudes and innovation. Acad. Manag. Rev. 2, 27–37.
Pillai, R., Sivathanu, B., Mariani, M., Rana, N.P., Yang, B., Dwivedi, Y.K., 2022. Adoption of AI-empowered industrial robots in auto component manufacturing companies. Prod. Plann. Control 33, 1517–1533.
Plewa, C., Troshani, I., Francis, A., Rampersad, G., 2012. Technology adoption and performance impact in innovation domains. Ind. Manag. Data Syst. 112, 748–765.
Priem, R.L., Butler, J.E., 2001. Is the resource-based "View" a useful perspective for strategic management research? Acad. Manag. Rev. 26, 22–40.
Pumplun, L., Tauchert, C., Heidt, M., 2019. A new organizational chassis for artificial intelligence - exploring organizational readiness factors. ECIS 2019 Proceedings 1–15.
Rafferty, A.E., Jimmieson, N.L., Armenakis, A.A., 2013. Change readiness. J. Manag. 39, 110–135.
Rammer, C., Fernández, G.P., Czarnitzki, D., 2022. Artificial intelligence and industrial innovation: evidence from German firm-level data. Res. Pol. 51, 1–15.
Rialti, R., Zollo, L., Ferraris, A., Alon, I., 2019. Big data analytics capabilities and performance: evidence from a moderated multi-mediation model. Technol. Forecast. Soc. Change 149, 1–35.
Roblek, V., Meško, M., Krapež, A., 2016. A complex view of Industry 4.0. Sage Open 6, 1–11.
Rogers, E.M., 1983. Diffusion of Innovations, third ed. Free Press, New York, NY, p. 453.
Rogers, E.M., 1995. Diffusion of Innovations, fourth ed. Free Press, New York, NY.
Rogers, E.M., 2003. Diffusion of Innovations, fifth ed. Free Press, New York, NY, p. 551.
Rusly, F.H., Corner, J.L., Sun, P., 2012. Positioning change readiness in knowledge management research. J. Knowl. Manag. 16, 329–355.
Russell, S.J., Norvig, P., 2010. Artificial Intelligence: a Modern Approach, third ed. Prentice-Hall, Upper Saddle River, NJ.
Sanchez, M., Exposito, E., Aguilar, J., 2020. Autonomic computing in manufacturing process coordination in industry 4.0 context. Journal of Industrial Information Integration 19, 1–16.
Schryen, G., 2013. Revisiting IS business value research: what we already know, what we still need to know, and how we can get there. Eur. J. Inf. Syst. 139–169.
Sharma, P., Shah, J., Patel, R., 2022. Artificial intelligence framework for MSME sectors with focus on design and manufacturing industries. Mater. Today Proc. 62, 6962–6966.
Sirmon, D.G., Hitt, M.A., Ireland, R.D., Gilbert, B.A., 2011. Resource orchestration to create competitive advantage: breadth, depth, and life cycle effects. J. Manag. 37, 1390–1412.
Sjödin, D., Parida, V., Palmié, M., Wincent, J., 2021. How AI capabilities enable business model innovation: scaling AI through co-evolutionary processes and feedback loops. J. Bus. Res. 134, 574–587.
Steininger, D., Mikalef, Patrick, Adamantia, P., Ana, O.d.G., 2022. Dynamic capabilities in information systems research: a critical review, synthesis of current knowledge, and recommendations for future research. J. Assoc. Inf. Syst. Online 447–490.
Stevens, G.W., 2013. Toward a process-based approach of conceptualizing change readiness. J. Appl. Behav. Sci. 49, 333–360.
Sun, H., 2013. A longitudinal study of herd behavior in the adoption and continued use of technology. MIS Q. 37, 1013–1041.
Tariq, M.U., Poulin, M., Abonamah, A.A., 2021. Achieving operational excellence through artificial intelligence: driving forces and barriers. Front. Psychol. 12, 1–15.
Teece, D.J., Pisano, G., Shuen, A., 1997. Dynamic capabilities and strategic management. Strateg. Manag. J. 18, 509–533.
Toorajipour, R., Sohrabpour, V., Nazarpour, A., Oghazi, P., Fischl, M., 2021. Artificial intelligence in supply chain management: a systematic literature review. J. Bus. Res. 122, 502–517.
Tornatzky, L.G., Fleischer, M., 1990. The Processes of Technological Innovation. Lexington Books, Lexington, Mass.
Trakadas, P., Simoens, P., Gkonis, P., Sarakis, L., Angelopoulos, A., Ramallo-González, A. P., Skarmeta, A., Trochoutsos, C., Calvo, D., Pariente, T., Chintamani, K., Fernandez, I., Irigaray, A.A., Parreira, J.X., Petrali, P., Leligou, N., Karkazis, P., 2020. An artificial intelligence-based collaboration approach in industrial IoT

manufacturing: key concepts, architectural extensions and potential applications. Sensors 20.
Turner, C.J., Emmanouilidis, C., Tomiyama, T., Tiwari, A., Roy, R., 2019. Intelligent decision support for maintenance: an overview and future trends. Int. J. Comput. Integrated Manuf. 32, 936–959.
Uren, V., Edwards, J.S., 2023. Technology readiness and the organizational journey towards AI adoption: an empirical study. Int. J. Inf. Manag. 68, 1–12.
Venkatesh, V., Morris, M.G., Davis, G.B., Davis, F.D., 2003. User acceptance of information technology: toward a unified view. MIS Q. 27, 425–478.
Verganti, R., Vendraminelli, L., Iansiti, M., 2020. Innovation and design in the age of artificial intelligence. J. Prod. Innovat. Manag. 86, 1–16.
Vernim, S., Bauer, H., Rauch, E., Ziegler, M.T., Umbrello, S., 2022. A value sensitive design approach for designing AI-based worker assistance systems in manufacturing. Procedia Comput. Sci. 200, 505–516.
Wang, H., Qiu, F., 2023. AI adoption and labor cost stickiness: based on natural language and machine learning. Inf. Technol. Manag. 1–22.
Weiner, B.J., 2009. A theory of organizational readiness for change. Implement. Sci. : ISCUS 4, 1–9.
Wieringa, J., Kannan, P.K., Ma, X., Reutterer, T., Risselada, H., Skiera, B., 2021. Data analytics in a privacy-concerned world. J. Bus. Res. 122, 915–925.
Williams, G., Meisel, N.A., Simpson, T.W., McComb, C., 2022. Design for artificial intelligence: proposing a conceptual framework grounded in data wrangling. J. Comput. Inf. Sci. Eng. 22.
Wu, F., Mahajan, V., Balasubramanian, S., 2003. An analysis of E-Business adoption and its impact on business performance. J. Acad. Market. Sci. 31, 425–447.
Wuest, T., Romero, D., Cavuoto, L.A., Megahed, F.M., 2020. Empowering the workforce in Post–COVID-19 smart manufacturing systems. Smart and sustainable manufacturing systems 4, 1–5.
Zavodna, L.S., Überwimmer, M., Frankus, E., 2024. Barriers to the implementation of artificial intelligence in small and medium sized enterprises: pilot study. JEM 46, 331–352.
Zhan, Y., Xiong, Y., Han, R., Lam, H.K., Blome, C., 2024. The impact of artificial intelligence adoption for business-to-business marketing on shareholder reaction: a social actor perspective. Int. J. Inf. Manag. 76, 1–15.
Zmud, R.W., 1982. Diffusion of modern software practices: influence of centralization and formalization. Manag. Sci. 28, 1421–1431.